VISUALISATION OF DATA TO OPTIMISE STRATEGIC DECISION MAKING

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The Department of Information Systems

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By

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Plagiarism Declaration

1. I know that plagiarism is wrong. Plagiarism is to use another's work and pretend that it is one's own.

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6. I have not falsified or manufactured any data, and declare that all data was ethically collected.

7. Parts of this thesis have been included in assignments during the Masters Information Systems course-work conducted in 2016, including Systems Thinking, the Critical Assignments, Literature reviews, Journals and Proposals.

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1 INTRODUCTION

1.1 Purpose of the study

The purpose of this research was to explain the principles that should be adopted when developing data visualisations for effective strategic decision making.

1.1.1 *Main problem statement*

Big data is produced at exponential rates and organisational executives may not possess the appropriate skill or knowledge to consume it for rigorous and timely strategic decision-making (Li, Tiwari, Alcock, & Bermell-Garcia, 2016; Marshall & De la Harpe, 2009; McNeely & Hahm, 2014).

1.1.2 *Sub-problems*

Organisational executives, including Chief Executive Officers (CEOs), Chief Financial Officers (CFOs) and Chief Operating Officers (COOs) possess unique and differing characteristics including education, IT skill, goals and experiences impacting on his/her strategic decision-making ability (Campbell, Chang, & Hosseinian-Far, 2015; Clayton, 2013; Krotov, 2015; Montibeller & Winterfeldt, 2015; Toker, Conati, Steichen, & Carenini, 2013; Xu, 2014). Furthermore, data visualisations are often not “fit-for-purpose”, meaning they do not consistently or adequately guide executive strategic decision-making for organisational success (Nevo, Nevo, Kumar, Braasch, & Mathews, 2015). Finally, data visualisation development currently faces challenges, including resolving the interaction between data and human intuition, as well as the incorporation of big data to derive competitive advantage (Goes, 2014; Moorthy et al., 2015; Teras & Raghunathan, 2015).

1.1.3 *Research Questions*

Based on the challenges identified in section 1.1.1 and 1.1.2, the researcher has identified 3 research questions.

RQ1: What do individual organisational executives value and use in data and data visualisation for strategic decision-making purposes?

RQ2: How does data visualisation impact on an executive’s ability to use and digest relevant information, including on his/her decision-making speed and confidence?

RQ3: What elements should data analysts consider when developing data visualisations?

1.2 Rationale

The study will provide guidance to data analysts on how to develop and rethink their data visualisation methods, based on responses from organisational executives tasked with strategic decision-making. By performing this study, data analysts and executives will both benefit, as data analysts will gain knowledge and understanding of what executives value and use in data visualisations, while executives will have a platform to raise their requirements, improving the effectiveness of data visualisations for strategic decision-making.

1.3 Research Method

Qualitative research was the research method used in this research study. Qualitative research could be described as using words rather than precise measurements or calculations when performing data collection and analysis and uses methods of observation, human experiences and inquiry to explain the results of a study (Bryman, 2015; Myers, 2013). Its importance in social science research has increased, as there is a need to further understand the connection of the research study to people's emotions, culture and experiences (Creswell, 2013; Lub, 2015). This supports the ontological view of the researcher, which is an interpretivist's view (Eriksson & Kovalainen, 2015; Ormston, Spencer, Barnard, & Snape, 2014). The epistemology was interpretivism, as the researcher interviewed executives and data analysts (Eriksson & Kovalainen, 2015; Ritchie, Lewis, Nicholls, & Ormston, 2013). Furthermore, literature relating to decision-making supported the researcher's interpretivist view, as people generally make decisions based on what they know at the time (Betsch & Haberstroh, 2014). Therefore, the researcher cannot separate the participant from his/her views (Dhochak & Sharma, 2016).

The population for this research comprised of 13 executives tasked with strategic decision-making, as well as 4 data analysts who are either internal (permanent employees) or external (consultants) of the organisation within the private sector. To demonstrate that the number of participants used was appropriate based on saturation reach, Brown's doctoral thesis (2005) on *"Espoused theory versus theory in use: the case of strategic information systems planning"*, used 7 executives based on saturation reach (Brown, 2005; O'Reilly & Parker, 2012). The reasoning for private sector focus was based on the overall data management maturity in comparison to the public sector's, specifically in data completeness and accuracy (Mphatswe et al., 2012). As the research study was predominantly focused on executive responses, more executive participants (13) were used compared to data analysts (4). However, data analysts remained an important component, as their past involvement in data visualisation design and development provided additional insights into data visualisation success.

Maximum variation was used to prevent sampling bias (Palinkas et al., 2015; Seidman, 2013). The sample considered diversity factors including the participant's job position and years within the organisation. Race and gender were omitted based on the sensitivity of obtaining such data within the South African context (Daniels, 2016). Judgement was applied to ensure that an accurate sample representative of the study was drawn (Gideon, 2012).

The predominant research approach and instrument used for data collection was semi-structured interviews (Brinkmann, 2014; Galletta, 2013). Semi-structured interviews allowed the interviewee (executives and data analysts) to respond to the topic and questions in dialogue form, rather than closed questioning (Brikci & Green, 2007). Thus, by performing a semi-structured interview, additional sets of information may come to light that may be missed or hidden when performing only survey and questionnaire methods, which could be further queried (Knapp, Hall, & Horgan, 2013).

The first interviewee was purposely selected to test the interview questions, as the participant not only possessed the knowledge, but also had good communication skills, an open and non-defensive nature and had an interest in participating in the research study (Bryman & Bell, 2015). Based on the interviewee's response, two questions were reformulated into one, while the remaining questions remained unaffected. This second set of questions was used as a set of guidelines, which provided for improvisation in all subsequent interviews.

Once the data was collected, thematic analysis identifying commonalities and differences within the data was performed (Braun & Clarke, 2006; Vaismoradi, Turunen, & Bondas, 2013). Relationship analysis was introduced to determine why certain explanations were evident, and a coding scheme was applied to determine if the problem statements had been addressed (Brikci & Green, 2007).

Reliability was based on the ability to provide sufficient evidence of the procedures used within the research process, while measurement validity was based on the accuracy of the participants' responses as recorded by the researcher (Anfara, Brown, & Mangione, 2002; Ritchie et al., 2013). The researcher also adjourned their prior perceptions and philosophies to provide a non-biased data collection and analysis strategy (Stelter, 2010). The researcher also remained open-minded and consistently used all input provided by the participants (Anfara et al., 2002).

1.4 Context of the study

Strategic decision-making is a process of making decisions that can change the scope and direction of the organisation, as opposed to operational decisions which consider short-term goals (Shivakumar, 2014). A strategic decision allows an organisation to achieve a strategic pillar in its vision, by implementing an action (the decision outcome) in response to situational factors or circumstances (Eden & Ackermann, 2013). The effect of incorrect strategic decisions can be catastrophic. For example, a commercial South African bank, African Bank Investments Ltd (ABIL), began its operations in the late 1990's as an unsecured lender, providing credit to low income earners (Pickworth, 2014). Due to the decision of ABIL to solely focus on the low-income segment of the population, it suffered losses arising from mounting bad debt which impacted on the ability of low income earners to repay their debt. As of June 2015, ABIL has been placed under business rescue (Donnelly, 2015).

Enter a new challenge, big data (Gandomi & Haider, 2015). Big data is voluminous, varied, must be used in a timely manner to enable competitive advantage, provide value and be built on integrity to be effective and beneficial in today's organisations (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Tamhane & Sayyad, 2015). Research performed on effectual decision-making identified the use of data and its analysis into meaningful and usable information as a core benefactor for informed and effective strategic decision-making (Weiner, Balijepally, & Tanniru, 2015). However, according to a survey performed in 2010 by Genesis Consulting, executives stated that they felt unprepared to deal with big data, causing their confidence in strategic decision-making to diminish (Gifford, 2010). This sentiment was again echoed a few years on (Gandomi & Haider, 2015). According to a study of decision types, it was identified that executives feel they lack the appropriate facts, the ability to perform constructive scenario analysis and are unable to review varying viewpoints adequately to make effective strategic decisions (Shivakumar, 2014). Increased data volume and complexity can also impact on the ability of executives to consume and interpret data (B. Brown, Chui, & Manyika, 2011).

Data visualisation has been identified as a beneficial decision enabler, used by executives after financial modelling techniques (Gifford, 2010). Data visualisation can be summarised as the representation of various forms of data, including structured, streaming, unstructured and semi-structured (Russom, 2013). Data visualisation uses graphics or other picture mediums to display and organise data in such a way that anyone, no matter his/her literacy level, can identify patterns and gaps more easily (Gatto, 2015; Jois, 2016). Thus, effective data visualisation can highlight new opportunities and create competitive advantage for long term growth and profit (Hirsch, Seubert, & Sohn, 2015).

In summary, the research study will explain what principles should be adopted when developing data visualisations to optimise strategic decision making.

1.5 Assumptions and Limitations

It was assumed that executives involved with the research study use data before making decisions, specifically those related to strategy implementation. This assumption was based on the reasoning that executives, who can impact an organisation's trajectory based on the strategic decision made, require relevant and reliable information before making these decisions (Posner, 2015). In the event that sufficient and adequate information is not available, negative decision consequences may result (Garbuio, Lovallo, & Sibony, 2015; Houghton, 2015).

The second assumption made was that executives are individuals who possess different IT and data related skills that impact on their ability to make data available and applicable to them in a quick and intuitive manner. This assumption was based on the reasoning that data has predominantly been managed by and resided within the information technology space, with limited interaction and understanding of other executive requirements (Kerzner, 2013). Thus, the argument to update executive IT and data knowledge across the executive spectrum is essential for organisational benefit, including decision-making (Haislip, Masli, Richardson, & Watson, 2015).

1.6 Ethical considerations

The researcher followed the prescribed University of Cape Town's (UCT) ethical process. Permission was obtained from the researcher's Supervisor, the Information Systems Ethics Co-ordinator, as well as the Ethics Committee Chair as shown in Figure 1.

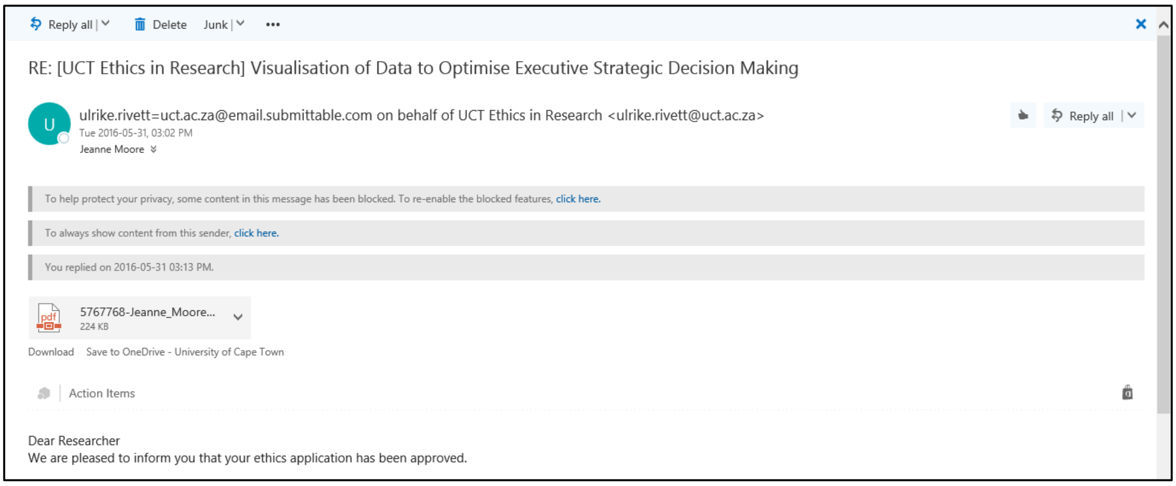


Figure 1 UCT Ethics Approval.

A consent form was provided to each interviewee and signed, protecting his/her confidentiality by explicitly stating that no personal or company information would be published at any point prior, during or after the research study (Stahl, Eden, Jirotka, & Coeckelbergh, 2014).

1.7 Structure of thesis

Following from Chapter 1 which has outlined the purpose, problem statements and context of the study, Chapter 2, provides the literature review which serves as the basis to formulate the research questions. Chapter 2 concludes with the conceptual framework developed by the researcher. Chapter 3 documents the research approach, explaining the research methodology used, the ontological and epistemological view of the researcher, the population used in the research study, data validity and reliability methods and finally, research assumptions and limitations. Chapter 4 covers the fieldwork in terms of the data analysis performed and findings derived from the analysis, additionally linking them to the literature review in Chapter 2. Chapter 5 provides a summary view of the research study, contemplation of findings and recommendations for further research. Figures and

Tables are documented within the main body of the thesis, and Appendix 1 appears after the References.

2 LITERATURE REVIEW

2.1 Introduction

Executives are not paid for doing things they like to do. They are paid for getting the right things done – most of all in their specific task, the making of effective decisions" (Drucker, 1966, p.167).

Over time, and as information technology (IT) has evolved, increasing volumes of data have been generated from varying sources, including manually documented notes, data stored within databases and publicly posted data via the internet (McAfee et al., 2012). As a result, organisations have had to rethink their data management and governance strategies for its ethical, effective and beneficial use (Mayer-Schönberger & Cukier, 2013). Today's executives cannot operate reactively, but are required to make rigorous decisions whilst understanding their organisation's internal strengths and weaknesses (Donovan, Güss, & Naslund, 2015). Executives must also anticipate the effect of future external social, legal, political and economic shifts in business practices to achieve organisational sustainability, competitive advantage and strategic growth (Donovan et al., 2015; Marques & Dhiman, 2016). The exponential increase in data volume and complexity, known as big data, is posing new organisational challenges, as traditional data management philosophies and infrastructure can no longer store, process and support big data needs (Marz & Warren, 2015). Whilst living in a fast paced world, how can organisational executives derive meaning from big data to make effective strategic decisions?

The relevance and development of data visualisation, aimed at making sense of big data, emerged in proportion to greater data volumes, faster production rates, faster technology processing capabilities and reduced storage costs (Dutta & Hasan, 2013). Data visualisation aims to present numeric and non-numeric data though the use of graphics or other picture mediums with the main purpose of displaying and organising data in such a way that anyone, no matter his/her literacy level, can identify patterns and gaps more easily, thus enabling quicker understanding and decision-making (Gatto, 2015; Jois, 2016). Organisations have identified value in big data and need to exploit it to enhance their competitiveness (Sim, 2014). Data visualisations provide a viable conduit to represent big data in an intuitive manner, allowing organisations to use big data to their advantage (Hirsch et al., 2015).

In order to collect literature, a systematic literature review was performed as per the approach adopted by Gomez, Baron and Fiore-Silfvast (2012). The approach included a content analysis of over 500 published articles, books, conference papers and journals post 2005 to 2017 within the Information Systems, Business Management and Psychology disciplines. Traditional data literature was obtained post 2005, while big data and data visualisation literature was obtained post 2010, with focus placed on literature published in 2015, 2016 and 2017 to highlight the most recent views of data visualisation (Okoli & Schabram, 2010). More specifically, literature was obtained from library databases including ACM Digital Library, IEEE Explore, Springer Link, ScienceDirect, Academic Search Premier and

PsychTESTS. The literature referenced in this paper was peer reviewed and where not, the researcher made a decision as to the relevancy of the paper based on year published, relevancy of topic discussed and author knowledge and experience (Vom Brocke, Simons, Niehaves, Riemer, Plattfaut, & Cleven, 2009). The key words searched included traditional data management, big data, data governance, strategic decision-making, data visualisation and cognition. These key words were derived from the research topic, which includes two dominant themes, namely strategic decision-making performed by executives and data visualisations which make use of design and cognitive elements to facilitate the process of sense-making (Gatto, 2015; Hirsch et al., 2015; Jois, 2016). Thereafter, literature obtained was developed into themes, enabling a logical and hierarchical flow of the literature (Gomez et al., 2012).

As a result of the systematic literature review, in terms of data visualisation, no specific mention of assessing hypotheses, propositions or research questions against organisational executive levels was identified (Borkin, Bylinskii, Isola, Sunkavalli, Oliva, & Pfister, 2013). In relation to strategic decision-making, it was evident that data was collected from front-line managers, divisional managers, and top executives in private and public organisations operating globally and within varied industries (Garbuio, Lovallo, & Sibony, 2015). The data collected for these literature reviews included online surveys and hence data relating to participant demographics could not be disseminated. This was partly due to personal information confidentiality requirements, but also to the accessibility of the survey from anywhere in the world (Liu, Sun, Ryoo, Rizvi, & Vasilakos, 2015). Although a clear picture could not be provided of the geographic location of the participants, it should be highlighted here that data visualisation has not been significantly explained within the South African context and the researcher was not able to find sufficient peer reviewed literature supporting the research topic. Therefore, this highlighted the need to further develop an understanding around the perceived value of data and its usefulness in strategic decision-making, using data visualisation as a supporting conduit within the South African context. Furthermore, research methods per literature reviewed were varied with quantitative methods representing the highest method used, accounting for over 60%, followed by qualitative and mixed methods with a combined total of approximately 30%. In some cases, no specific research method was documented, accounting for approximately 10%. In these instances, the intent of the paper was rather to review existing literature, use a mixed discipline approach, continue with research questions adopted in prior journals or articles, or to use only one specific theory. Therefore, the limited use of the qualitative research method provided further impetus for the researcher to adopt this approach in this paper.

As this research topic has two dominant subjects, namely (executive) strategic decision-making and data visualisation, recommendations identified from the literature reviewed was varied. At times, literature only referred to a specific element of the research topic, such as data visual elements or characteristics of strategic decision-making. However, the following recommendations were identified and increased the relevancy of the research topic, summarised below:

- When developing data visualisations, keep the audience in mind (Dasgupta, Poco, Wei, Cook, Bertini, & Silva, 2015; Teets, Tegarden, & Russell, 2010).
- When developing data visualisations, guide the user(s) attention to relevant and significant visual objects with similar marks, colour and size grouped together for easier and faster interpretation, as well as considering the impact these have on perceptual speed and verbal working memory which also have an impact on speed and interpretation (Gramazio, Schloss, & Laidlaw, 2014; Dasgupta et al., 2015; Patterson, Blaha, Grinstein, Liggett, Kaveney, Sheldon, & Moore, 2014; Toker et al., 2013).
- When developing data visualisations, focus on the message that is to be portrayed and make it independent of the data visualisation itself (Dasgupta et al., 2015).
- Strategic decisions require not only the aspects impacting the decision itself, but dialogue between other decision-makers, as well as consideration of internal and external factors to make the decision effective (Garbuio et al., 2015; McLeod & Childs, 2013; Shepherd & Rudd, 2014).
- The Cynefin framework should be adopted as a sense-making tool for organisational Executives, formulating a base for different decision-making possibilities, including strategic decisions, guiding thoughts and ideas, viewing situations at various angles and identifying cause and effect, not just in terms of problem categorisation. Applying these paradigms into strategic decision-making will provide the value of the framework to organisational Executives (Gorzeń-Mitka & Okręglicka, 2014; McLeod & Childs, 2013; Puik & Ceglarek, 2015).

2.2 Background discussion

2.2.1 *Data defined*

Data has been generated in various forms and used for a variety of purposes over many centuries. Data has no meaning when contained in isolation, while information provides meaning to the decision-maker by correlating and integrating data within a context (Świgoń, 2011). Knowledge is thereafter generated by grouping information together which can add value to the decision-maker, such as solving a problem (Mandinach et al., 2006). Today, data has become notably embedded in our daily lives, propelled by technological advances such as social media platforms.

In the enterprise domain, data has traditionally been synonymous with structured data, capable of being distinctly and clearly identified, categorised, stored and queried (Kaur & Monga, 2015). Its nature and type were homogenous, such as text and was derived from limited sources such as relational databases (Siddiqa et al., 2016). Due to the evolution of IT which created platforms that communicate data in new and challenging ways, big data has become the new term, or phenomenon, which describes the nature of data in current times (De Mauro, Greco, & Grimaldi, 2015). Big data is classified into structured, semi-structured, unstructured and streaming data, and if used collectively is termed as multi-structured data (Russom, 2013). Unstructured data is irregular in nature and cannot be grouped or arranged in a methodical manner, such as photographs and videos (Kaur & Monga, 2015). Semi-structured data encompasses data which cannot be stored in a relational database but can be organised in some manner, for example, XML documents (G. Li, Ooi, Feng, Wang, & Zhou, 2008). Streaming data relates to transferring data at high speeds and can come from a variety of sources including twitter feeds (Zliobaite, Bifet, Pfahringer, & Holmes, 2014). The term big data has often been criticised for its incorrect assumption that previous data was "small" and that the size of big data is the only challenge that must be solved, which is untrue (Nasser & Tariq, 2015).

Big data predominantly correlates itself with increased volume, velocity and variety (McAfee et al., 2012). However, additional big data attributes that impact on decision-making include data value and veracity (Tamhane & Sayyad, 2015). Volume refers to the amount or size of data produced, velocity refers to the time in which data must be acted upon for benefits realisation and variety refers to data heterogeneity in terms of its type and representation (Jagadish et al., 2014; McNeely & Hahm, 2014). Value refers to how data can be used to leverage competitive advantage while veracity refers to data quality, accuracy, integrity and data management consistency (Tamhane & Sayyad, 2015). According to Tole (2013), decisions need to be based on relevant and quality data, as not all data collected may be relevant to the decision at hand, thus highlighting the significance of data veracity (Tole, 2013). Value is also considered important due to the business advantages it delivers in terms of the decision-making process (Bijker & Hart, 2013).

In summary, Figure 2 highlights the key differences between traditional data and big data:

Traditional Data	Big Data
Structured data	Structured, semi-structured, unstructured and streaming data (multi-structured)
Statistical analysis with known conditions to answer questions	Discovery driven analytics with unknown conditions to answer questions
Terabytes of data	More than terabytes of 'messy' data
Batch oriented analytics	Real-time analytics
Text and numbers based	Includes graphical, audio and other streaming and unstructured data
Relational data model	Not easy to form structured relationships between data

Figure 2 Difference between traditional data and big data (Rajagopalan & Vellaipandiyan, 2013).

2.2.2 *Governing data*

One strategy to data management encompasses the data lifecycle. This implies that data has a finite beginning and end, following the processes of data acquisition, recording, extraction, cleansing, integration, aggregation, analysis, interpretation, purging and communication (Sinaeepourfard et al., 2016). Data lifecycle management has been defined as the storage of data using infrastructure that is most applicable to derive business value as it changes over time (Yoshida, 2009). The main objective of data lifecycle management is to instil data quality, thus allowing further sustainability of data in its applications, such as in decision-making (Descher et al., 2009).

Overarching the data lifecycle management process is data governance. Data governance identifies the significance of other data attributes including ethical considerations, regulatory requirements and data quality (Weber, Otto, & Österle, 2009). As lessons from past corporate failures such as Enron come to light, regulations such as Sarbanes Oxley highlighted the need for control over information reporting and to leverage data assets in an appropriate manner for ethical use (Khatri & Brown, 2010). A clear distinction between data governance and data management must be made here. Data governance identifies the decisions that must be made in order to manage information technology (IT) in the most appropriate manner including responsible and accountable parties (Khatri & Brown, 2010). Data management is rather centred on the implementation of decisions including how data is shared, protected, stored and retained (Buys & Shaw, 2015). In order to develop a data governance framework, Khatri and Brown (2010) identified five interdependent decision domains, namely data principles, data quality, metadata, data access and data lifecycle (Fruehauf, Al-Khalifa, Coniker, & Grant Thornton, 2015). Data principles encompass the role of data as an asset, data quality establishes data requirements and intended use, metadata describes the meaning of the data element, data access identifies who and how data can be accessed and finally, data lifecycle identifies the phases of data from creation to retirement (Khatri & Brown, 2010). The framework also identifies the role-players accountable at each domain decision and some questions that should be asked (Khatri & Brown, 2010). However; the framework does not specify the actual methodology of how to implement the data governance framework, which is left to the discretion of the implementer. Furthermore, as per Figure 3, executive accountability of these domains is not specified. For the data quality domain, a large proponent of data governance, no committee or executive is defined (Mendes Sampaio, Dong, & Sampaio, 2015).

Data Governance Domains	Domain Decisions	Possible Roles
Data Principles	• How is data used within the business? • What opportunities exist to share and reuse data within the organisation? • What influence do regulators have on business data use? • What mechanisms are used to communicate the business use of data in an ongoing manner? • What are the desirable behaviours for employing data as assets?	Data owner/trustee Data custodian Data steward Data producer/ supplier Data consumer Enterprise Data Committee/Council
Data Quality	• What are the standards for data accuracy, timeliness, completeness and credibility? • How will data quality be established and communicated within the organisation? • How will data quality and the program be evaluated?	Data owner Subject matter expert Data quality Manager Data quality analyst
Metadata	• How and what is documented regarding data semantics? • How will data be consistently defined and model for interpretability? • How will metadata be updated in a timely manner?	Enterprise data architect Enterprise data modeller Data modelling engineer Data architect Enterprise Architecture Committee
Data Access	• What is the business value of data? • How will risk assessment be conducted on an ongoing basis? • How will results of assessments be incorporated into overall monitoring? • What are the data access standards and procedures? • What is the program for periodic monitoring and audits? • How is security awareness and education disseminated? • What is the back-up and recovery program?	Data owner Data beneficiary Chief Information Security Officer (CISO) Data security officer Technical security analyst Enterprise Architecture Development Committee
Data Lifecycle	• How is data inventoried? • What is the program for all data types regarding definition, production, retention, and retirement? • How do compliance requirements affect data retention?	Enterprise data architect Information chain manager

Figure 3 Framework for data governance (Khatri & Brown, 2010).

Having understood traditional data, big data and data governance, what are the issues or challenges of big data that impact decision-making? Figure 4 highlights some of the issues currently faced by organisations within the realm of big data.

General Challenges	Solution	Reference
Processing power: data volume is superseding computational processing power resulting in Moore's Law becoming obsolete.	New technology is required to balance processing ability without negatively impacting on performance.	(Ammu & Irfanuddin, 2013)
Data volume	Cloud computing	(Armbrust et al., 2010)
Timely analytical capabilities of stored data.	Index structures must be agreed upon and created ahead to identify new criteria types more quickly.	(Ammu & Irfanuddin, 2013)
Supplementary information (meta-data) supporting data presentation.	Index structures must be agreed upon and created ahead to identify new criteria types more quickly.	(Ammu & Irfanuddin, 2013; Nasser & Tariq, 2015)
Data Quality	Implement big data governance policies to include standards for data accuracy, timeliness, completeness, credibility, data quality establishment, communication and evaluation.	(Jagadish et al., 2014; Khatri & Brown, 2010)
Regulatory requirements	Infuse big data governance policies with regulatory requirements in relation to customers, suppliers, employees and business stakeholders for all regions/locations where interaction is performed.	(Nasser & Tariq, 2015; Tallon, 2013)
Data security and access	Deploy risk and control strategies to secure data and queries such as encryption techniques, implement security technology related to big data and implement security and privacy of correlative big data. Include such procedures within the data governance policy.	(Ou, Qin, Yin, & Li, 2016)

Data Life-cycle Challenges	Solution	Reference
Data acquisition and recording: filtering, metadata generation and trustworthiness.	Identify filters that must be applied to data when acquired from data sources to reduce the amount of irrelevant data stored. Identify metadata to be used in analytical scenarios.	(Jagadish et al., 2014; Nasser & Tariq, 2015)
Data extraction and cleaning: effectively utilising unstructured and streaming data for analytics, error handling.	Automation of the data rules and metadata.	(Nasser & Tariq, 2015)
Data integration and aggregation: data heterogeneity and automating of integration and aggregation.	No definitive solution, but there is a need to move from unstructured to structured data for analysis.	(Jagadish et al., 2014; Nasser & Tariq, 2015)
Interpretation: wrong modelling, erroneous data, audience freedom to change presentations based on new assumptions.	Rich interactive visualisations which promote drill-down capabilities, providing information about the presentation itself, allowing errors to be detected and models to be queried.	(Nasser & Tariq, 2015)

Figure 4 Big data challenges and solutions.

As a result of the debate regarding how big data should be managed for the purpose of benefit and value in strategic decision-making, theories relating to big data management and governance have been identified. Big data management includes storage, pre-processing, processing, security, governance, integration, warehousing and quality considerations (Siddiqa et al., 2016). The main objective, as with traditional data management, is to enhance data quality and accessibility for decision-making and productivity (Morabito, 2015). Big data management is a new discipline and many frameworks and theories have been developed, some of which are discussed below (Rajagopalan & Vellaipandiyan, 2013; Merino, Caballero, Rivas, Serrano, & Piattini, 2016; Priebe & Markus, 2015).

Firstly, a theoretical big data framework proposed for government related institutions is the big data analytical stack, documented in Figure 5 (Rajagopalan & Vellaipandiyan, 2013). This big data framework can be categorised into four dominant components: resource and scheduling management, data organisation and management, analytics and discovery and reporting (decision support and visualisation). However, the big data analytical stack talks more to the technology that can be used for each quadrant, but not to other properties and concerns relating to data governance, data quality and data security previously reviewed in traditional data lifecycle and governance frameworks.

Resource management • Resource utilisation, • Resource performance, • Data sharing • Operational processes • Resource maintenance.	**Data organisation and management** • Software and processes required to organise structured and unstructured data.
Data analytics and discovery • Batch and real-time data analytics	**Reporting** • Reporting and dashboards • Visualisation • Analytics and Advanced Analytics such as predictive, behavioural, comparative, fraud, risk and sentimental analysis.

Figure 5 Big Data Framework - Big Data Analytical Stack (Rajagopalan & Vellaipandiyan, 2013).

Secondly, the 3As Data Quality-in-Use model looks further than big data and identifies the need to include a conceptual and technological stack that also focuses on raw and processed data, data storage, data management, data processing and analytics (Merino et al., 2016). This 3As Data Quality-in-Use model purports that data quality provides business value and hence the context of the data's use becomes significant (Lew, Olsina, & Zhang, 2010). The 3As Data Quality-in-Use model encompasses three aspects of adequacy, namely contextual (relevant, complete, unique, credible, confidential, compliant and semantically interoperable and accurate), operational (available, authorised, portable, precise, efficient and traceable) and temporal (current, timely updated, frequent and time-concurrent) (Merino et al., 2016). The 3As Data Quality-in-Use model also identifies that data quality programs for big data require real-time processing, managing a variety of data types of which the data relationships may not be understood (Merino et al., 2016).
Finally, a big data framework proposed for data intensive projects, data science and big data governance is the Business Information Modelling (BIM) methodology (Priebe & Markus, 2015). The BIM methodology encompasses not only the physical and logical data models but also the semantic business information model, which has been described as a catalogue of information pieces (Priebe & Markus, 2015). BIM considers the subject areas, entities, attributes and attribute definitions of data documented within the Accurity Glossary artefact describing the data source, store, lineage, name, description, shared business vocabulary and classification (Ferguson, 2015; Priebe & Markus, 2015). However; the BIM methodology has predominantly been tested in data warehouse scenarios, which contains traditional data as opposed to big data (Priebe & Markus, 2015).

Existing big data management frameworks highlight the need for future development in relation to structured management methodologies. Although significant strides have been made to explain and explore big data management, they do not encompass all objective and subjective data needs from data retrieval to retirement, including all governance requirements (Merino et al., 2016; Rajagopalan & Vellaipandiyan, 2013; Priebe & Markus, 2015).

2.2.3 *Benefit of data for strategic decision-making*

Executives possess different information technology (IT) skills and are directed by varying sub strategies resulting in differing organisational visions (Clayton, 2013; Krotov, 2015). This leads to executives having different data knowledge and skills, which may not be consistent across the leadership level for sound decision-making (Xu, 2014). Therefore, a "one-size-fits-all" approach to data presentation for decision-making is counterproductive and inhibiting (Nevo et al., 2015).

Literature also identified the use of data and its analysis into meaningful and usable information as a core benefactor of effective decision-making (Weiner et al., 2015). Data in decision-making must "*acknowledge both subjective and objective factors and blend analytical with intuitive thinking, requiring only as much information and analysis as is necessary to resolve a particular dilemma and encouraging and guiding the gathering of relevant information and informed opinion*" (Hammond, Keeney, & Raiffa, 2015, p.4).

Regarding decision-making within the organisational and executive context, data driven decision-making (D3M) was identified as a value-adding praxis (Cao, 2010). D3M uses data through enhanced analytics and related information management structures to provide evidence-based information for end-user decision-making (Duggan, 2014). Therefore, the process of decision-making is performed based on data analysis (Provost & Fawcett, 2013). However, a potential limitation of the data driven decision-making approach is that decision-makers can become too metric driven and may not open themselves up to the thinking that drives innovation (Duncan & Buytendijk, 2015; Tickle et al., 2016). This sentiment is shared by Bouyssou et al., (2013) who highlight the importance of not only using data to enable investigation, but one must also apply sensory and cognitive processes to aid effective decision-making (Bouyssou, Dubois, Prade, & Pirlot, 2013). Regardless, based on a survey of 179 publicly trading firms by Massachusetts Institute of Technology (MIT) and Penn's Wharton School, D3M correlates to improved productivity, higher return on assets, asset utilisation, equity and market value (Brynjolfsson, Hitt, & Kim, 2011; Provost & Fawcett, 2013).

Strategic management theory identifies the type of data executives use to make strategic decisions (Bryson, 2011). Strategic management encompasses five steps, firstly identifying the organisation's vision, mission and goals, secondly identifying external opportunities and threats, thirdly identifying internal organisational strengths and weaknesses, fourthly developing strategies in line with the organisational vision and finally, implementing the agreed strategy (Hill, Jones, & Schilling, 2014). This planning process demonstrates the significance of internal and external data gathering to support executive strategic decision making. However; a concept called "disinterested dialogue" describes executive strategic decision-making as a process using both quantitative and qualitative factors (Garbuio et al., 2015). Results of a disinterested dialogue study, which surveyed 634 strategic decisions across multiple industries including legal, financial, technology, manufacturing, business and telecommunications around the world, showed that key properties of effective strategic decision-making include not only the analysis of quantifiable financial risks and returns, but also require conversations regarding the actual decision itself using the skills and knowledge of others/peers to discuss the decision (Garbuio et al., 2015). Therefore, executives use internal and external data, experience and instinct after considering factual and quantitative data before making the final decision (Marsh, Sloan McCombs, & Martorell, 2010; Steiner, 2010).

Figure 6 explains a data driven decision-making framework using data as the core element within a hierarchical structure, much like the organisational structure, identifying cognitive processes that impact on the decision-making process

(Mandinach & Jackson, 2012). The framework defines data as a raw constituent which has no meaning when contained in isolation (Cios, Pedrycz, & Swiniarski, 2012; Travica, 2014). Information provides meaning to the decision-maker by correlating data within a context and knowledge is a grouping of information that has value or provides benefit to the decision-maker, such as solving a problem (Larose, 2014). The framework provides six cognitive processes which enable the decision-maker to reach the decision once knowledge is acquired (Mandinach & Jackson, 2012). Firstly, data must be collected (Sapsford & Jupp, 2006). The collection process is at the discretion of the decision-maker who decides what data and from which sources is relevant (McAfee et al., 2012). This first step is often driven by the decision-maker's question(s) that require answering and what is available. Not all data is available and therefore the decision-maker must consider the necessity of the data to the task at hand. The data must then be organised or categorised in some manner in order to initiate sense-making. By performing this process, data is translated into information, of which meaning can be derived (Chowdhury, 2010). Thereafter, the decision-maker can begin analytical processes, testing the correctness of initial hypotheses (Mandinach et al., 2006). The next step is to summarise what has been analysed. The summary of information should be directed by the initial objective of what the consumer hopes to achieve. The summary information could provide varying scenarios and dimensions to a particular problem. To produce knowledge, the decision-maker must synthesize or combine the information and prioritise the knowledge, often involving judgement based on the decision-maker's prior experiences (Siemens, 2014). Prioritisation ranks the knowledge by importance and hence the decision-maker can determine what areas require more focus than others (Mandinach et al., 2006). This then assists in identifying the appropriate decision to take, which can be implemented and the resulting impact monitored. The resulting impact can then be used as possibly initiating further tasks such as further data collection, creating an iterative cycle which results in decisions (Mandinach et al., 2006). This data driven decision-making framework also highlights a cyclical process of data planning, data implementation and data assessment and analysis, also identified and supported by the Means, Padilla and Gallangher's Conceptual Framework for data driven decision-making (Means, Padilla, & Gallagher, 2010).

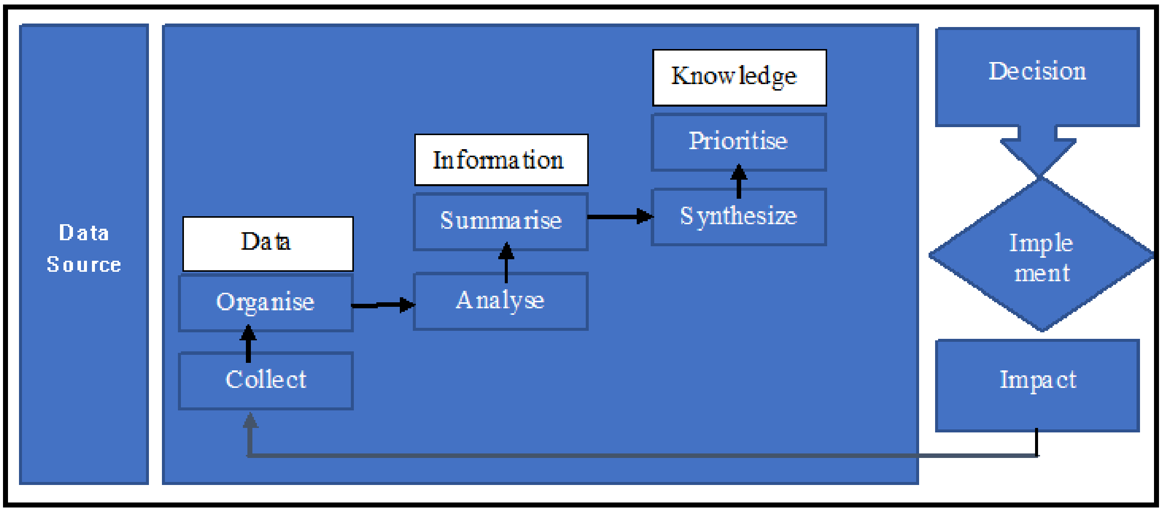


Figure 6 Framework for data driven decision-making (Mandinach et al., 2006).

Executives wish to know that the data they are using is reliable, timely and accurate (Sun, Luo, & Das, 2012). Trust theory supports the notion that the decision to place trust in something is driven by a person's mental attitude, prediction or evaluation of the item, the intention to delegate trust, as well as the behaviour or intentional act of trusting (He, Lai, Sun, & Chen, 2014). Factors such as motivation, willingness, ability, "know-how", a person's self-confidence, beliefs, opportunities, dangers, obstacles and safety all impact on a person's decision to trust (Castelfranchi & Falcone, 2010). In the context of South African decision-making, a study relating to data issues hampering effective decision-making was performed within a large retail organisation by the Cape Peninsula University of Technology Cape Town (Marshall & De la Harpe, 2009). This study, data issues within a business intelligence environment, was chosen by the researcher due to the organisation's size and importance within the economy, as well as its information technology capabilities (Grubliešič & Jaklič, 2015). Discrepancies between the data source and data store, over or understated data values, inconsistent or inaccurate data calculations, inconsistent data formats, data unavailability and a lack of infrastructure to fulfil new requirements were cited as significant data issues affecting the ability to trust and use data (Marshall & De la Harpe, 2009). Therefore, when presenting data, data source and pipeline accuracy, data definition and structure consistency, timely retrieval and data support are vital considerations for data trust and use (Akerkar & Sajja, 2016).

In terms of organisational decision-making, a framework known as the Cynefin framework identifies five domains, each representing a situation which an organisation may be faced (Snowden & Boone, 2007). Ordered domains are simple and complicated while unordered domains are complex and chaotic (Gorzeń-Mitka & Okręglicka, 2014). The centre domain represents disorder which represents the unknown (Czinki & Hentschel, 2016). Per the Cynefin framework, executive strategic decisions typically fall within the complex domain, due to the lack of clear cause and effect of the decision, as potentially new terrain is being explored (probed) and querying (of data) is required for information purposes. Therefore, the link between data and strategic decision-making, based on the characteristics of the complex domain, becomes apparent (Axelrod, 2015).

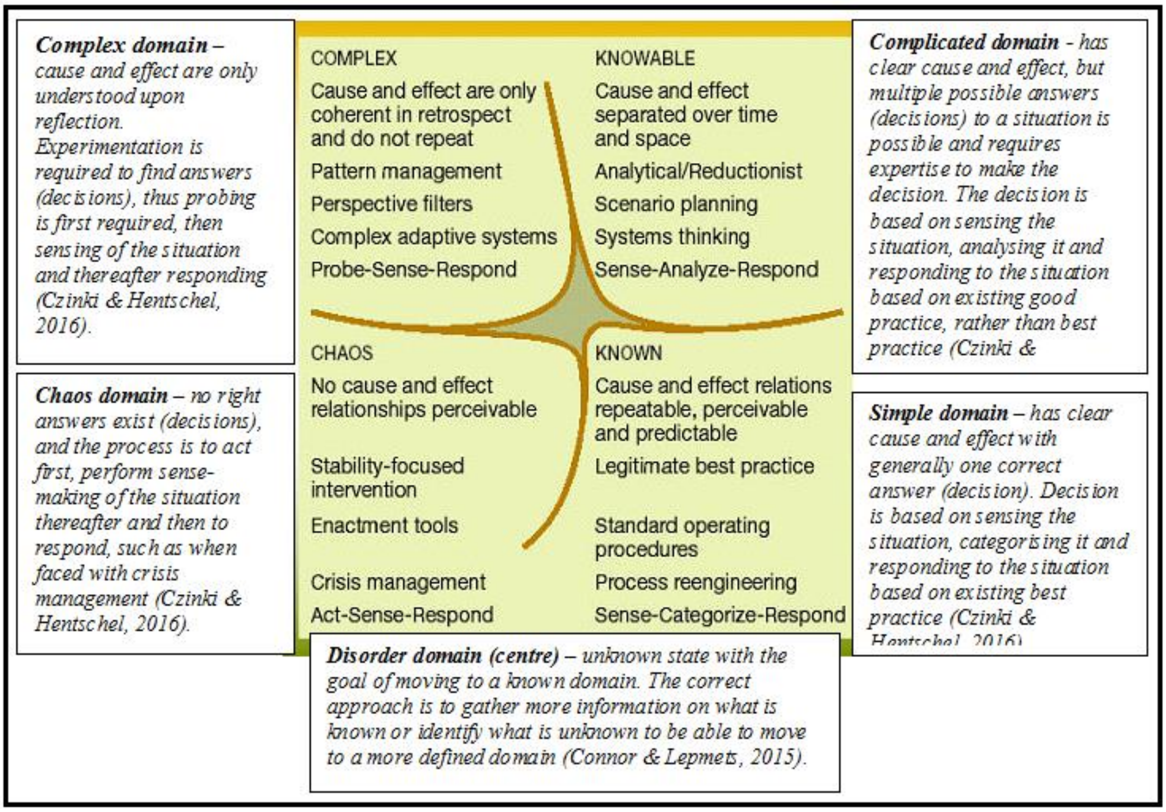


Figure 7 Cynefin framework for decision-making (Snowden & Boone, 2007).

It is important to note that one domain is not favoured over another; it simply helps to identify strategies based on the situation faced by the organisation (McLeod & Childs, 2013). Thus, the Cynefin framework is entrenched in creating meaning, whereby data serves as the platform for sense-making (Puik & Ceglarek, 2015). The Cynefin framework is used to support decision-making and strategy development in vigorous, challenging and complex environments (McLeod & Childs, 2013). The Cynefin framework argues against the outdated notion that decision-making is a linear exercise, whereby information is contained within a hierarchical structure and simple algorithms can be used to make good decisions (Katsikopoulos & Cherng-Horng Lan, 2011). Hierarchy is not conducive to the environment in which executives operate, as they function in complex environments, whereby varying factors can influence strategic decision-making (Houghton, 2015). This is further illustrated in Figure 8 depicting complex contextual variables (left of Figure 8), strategic decision-making process (SDMP) characteristics (middle of Figure 8) and SDMP outcomes (right of Figure 8).

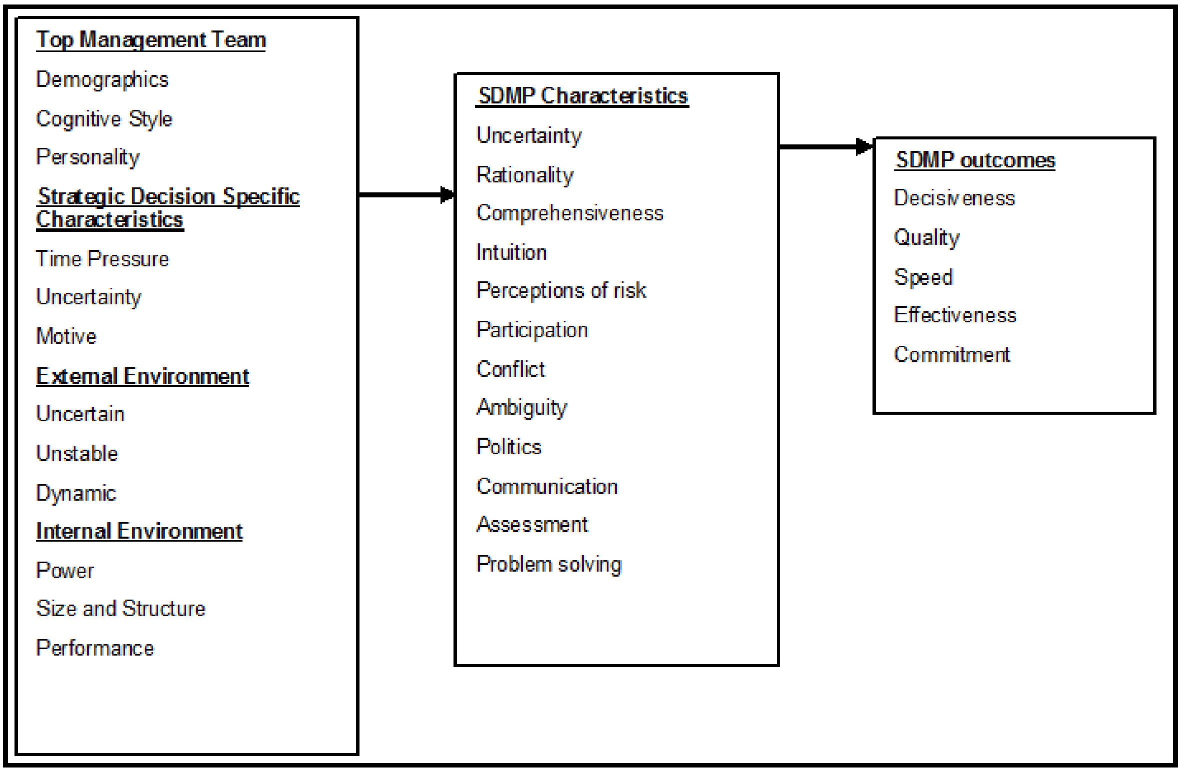


Figure 8 Variables in Strategic Decision Making (Shepherd & Rudd, 2014).

The question remains, with such decision-making theories and methods available, what has changed that hinders executives from displaying confidence, and thus achieving efficient and effective decision-making, in today's context? The effects of the big data phenomenon on the organisation as a whole and its ability to assimilate, certify, categorise, classify, process and store big data, which traditional data infrastructure, policies and views can no longer support can assist in answering this question (Moorthy et al., 2015). Therefore, the benefits of data to drive innovation, leading to competitive advantage, may be unreachable if not managed properly (Goes, 2014; Tallon & Pinsonneault, 2011).

Literature related to big data, big data governance, strategy formulation and decision-making identified what each concept was, including the advantages, disadvantages, challenges and opportunities of big data, its governance and how to approach strategy formulation and data driven decision-making. However; per the literature reviewed by the researcher, no clear guidance was provided in terms of what executives consider critical or valuable in data for strategic decision-making. This leads to research question one.

RQ1: What do individual organisational executives value and use in data and data visualisation for strategic decision-making purposes?

2.2.4 *Data visualisation*

Data visualisation is a methodically developed graphic which represents data in a manner that allows one to obtain insights, develop understanding, identify patterns, trends or anomalies faster and promote engaging discussions (Dasgupta et al., 2015). Data visualisation has been widely used as a tool for aiding understanding of complex phenomena by using technology to integrate graphic creation with image understanding and enabling more efficient communication (Wang, 2015). Literature has stated that visualisation development faces challenges, including adequate viewer interaction, to enable the connection between data and human intuition (Teras & Raghunathan, 2015). Therefore, data visualisations are often not "fit-for-purpose"; in other words, do not adequately guide executive decision-making. Today, data visualisation is used within organisations to enhance the decision-making process (Toker et al., 2013). As visualisation is a tool promoting understanding, it enhances the link between visualisation and sense-making (de Regt, 2014). In relation to big data, which adds another layer of complexity, data visualisation is significant in presenting and communicating complex data intuitively by assembling and summarising various forms and amounts of data for effective human information interpretation (Campbell et al., 2015; Dasgupta et al., 2015; Gatto, 2015). Data visualisation assists with sense-making by extrapolating meaning from complex datasets and uses the human visual system in order to create insight regarding conceptual information (Patterson et al., 2014; Reilly, 2014). A summary of the components in human cognition is identified in Figure 9. The human visual system consists of the eye and a portion of the brain. The eye acts as a camera taking the picture, while the brain performs complex image processing allowing an individual to make sense of what has been seen (Nercessian, Panetta, & Agaian, 2013). Thus, in summary, the benefits of visualisation are knowledge sharing by externalising internal understanding by improving thinking capacity and assisting in new idea formulation by lessening the working memory of a person and creating deeper relationship understanding (Li et al., 2016). This directly correlates to the data driven decision-making framework identified in Figure 6 (Mandinach et al., 2006), which highlights summarising and analysing as cognitive functions that must be applied to derive meaning from data.

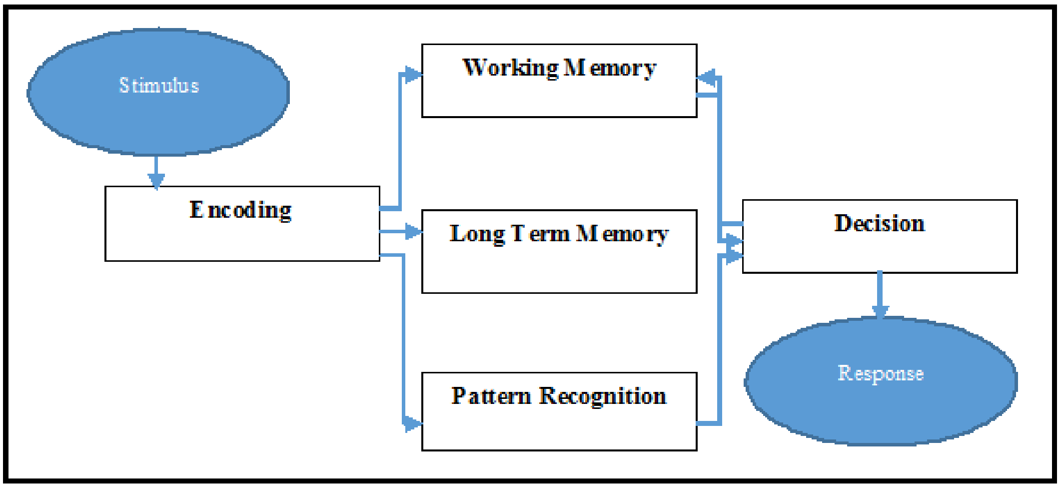


Figure 9 Overview of Human Cognition (Patterson et al., 2014).

Cognition is a mental process of information gathering and processing that aids reasoning and thus relates to sense-making (Helfat & Peteraf, 2015). Cognitive fit theory (CFT) and the proximity compatibility principle (PCP) can be used to explain how data visualisations can be effective for decision-making. CFT explains how best to present data in order to solve a problem effectively (John & Kundisch, 2015). The cognitive fit theory states that the problem-solving task, such as solving a strategic complexity, and the problem representation of the task involved, such as a data visual, contribute to the effectiveness of the problem-solving process (van der Land, Schouten, Feldberg, van den Hooff, & Huysman, 2013). The interaction between the problem-solving task and the problem representation creates a mental representation in the mind of the decision-maker, leading the decision-maker to solve the problem faster and more accurately when the problem representation fits the problem-solving task (Teets, Tegarden, & Russell, 2010). The cognitive fit theory identifies that a decision-maker uses two predominant tasks, the symbolic task and the spatial task (Dilla & Raschke, 2015). The symbolic task involves extracting very accurate and granular data values, whereas the spatial task reflects a holistic view of the problem and considers other factors such as subjective data (Pournajaf, Xiong, Sunderam, & Goryczka, 2014; Vessey, Zhang, & Galletta, 2006). The spatial task requires the decision-maker to formulate relationships between data elements, whereby perception plays a significant role in defining these relationships (Vessey et al., 2006). Supplementing cognition is perception which uses the eye for understanding and interpretation purposes (Prinz, 2010). The cognitive fit theory's use of spatial and symbolic tasks reflects the process of strategic decision making by executives, as executives use both objectivity and subjectivity to make strategic decisions (Teets et al., 2010).

PCP describes how related information must be shown or grouped together (Russ et al., 2014). PCP relates to the problem-solving task as task proximity and representation as display proximity (Murata & Akazawa, 2014). PCP identifies task proximity (problem-solving task) as having three levels of processing, namely integrative processing (high task proximity: tasks are combined computationally or through Boolean integration), non-integrative processing of *similar* tasks (lower proximity and sources of data are similar) and non-integrative/independent processing of *dissimilar* tasks whereby tasks are independent of one another. (Hegarty, 2011; Teets et al., 2010). Therefore, the degree of task proximity relates to similarity of the task. Further considerations within data visualisation include exploration, confirmation and production (Bertini & Lalanne, 2010). Exploration allows the decision-maker to identify patterns and trends from the data visual, identifying hypotheses that can be investigated, confirmation allows the decision-maker to substantiate or disprove the initial hypotheses and production tasks are the actions performed as a result of the confirmation supported by the data visual (Ward, Grinstein, & Keim, 2010). Display complexity, or problem representation as referred to in cognitive fit theory, refers to the perceptual similarity of the information sources to be displayed and states that data from similar sources should be displayed closer together (Lakens, Schneider, Jostmann, & Schubert, 2011). Display proximity is impacted by spatial integration, connections, source similarity, code homogeneity and configuration (Teets et al., 2010). PCP uses task proximity and display proximity in a relationship that is directly proportional, i.e. the higher the level of required integration, the higher the level of proximity the display should possess, where the final result is to reduce cognitive effort when making decisions (Teets et al., 2010).

Reviews of cognitive fit theory in relation to decision-making were found in the manufacturing sector and medical sector. However, reviews relating to organisational strategic decision-making were not as evident. The manufacturing scenario used cognitive fit theory in relation to short-term operational production line decisions (Teets et al., 2010). The medical scenario referred to patient treatment plans within a clinical decision support system (CDDS) and proved more relatable to organisational strategic decision-making (Chang, Kao, Wu, & Su, 2016). For the medical scenario, the healthcare professional receives subjective information from the patient which may relate to a variety of potential diagnoses (Houghton, 2015; Patel & Kannampallil, 2015). Six guidelines relating to the development of the solution (CDDS) using CFT were defined and can be adapted for the design of data visualisations presented to organisational executives, referred to as the solution in the medical scenario. The CDDS review stated that the solution should be closely aligned with the decision-maker’s problem-solving activities. Only relevant objective and subjective data should be presented and grouped or classified correctly to reduce cognitive workload and processing. The solution should allow for automated as opposed to manual data processing to reduce the decision-maker’s mental workload and the correct data format must be used to present objective and subjective data simply and concisely (Chang et al., 2016; Hammond et al., 2015). Where higher degrees of data complexity are evident, the solution must allow for supporting data to be easily accessible and understandable. The solution should infer the processes that fit the decision-maker’s cognitive mental models and finally, the solution should be flexible to allow the decision-maker the ability to use his/her own reasoning to draw his/her own conclusions (Chang et al., 2016).

Individual user characteristics, such as cognitive abilities, also impact on the ability of the individual to consume data visualisations (Zsambok & Klein, 2014). Cognitive abilities include: perceptual speed (speed when performing perceptual tasks), visual working memory (storage and manipulation capacity of visual and spatial information), verbal working memory (storage and manipulation capacity of verbal information), personality traits including locus of control (extent to which an individual believes that events are determined by their actions or by external forces) and finally, visual and domain expertise on interactive data visuals (preferential choice) (Acheson, Hamidi, Binder, & Postle, 2011; Dane, Rockmann, & Pratt, 2012; Koop & Johnson, 2013; Lefcourt, 2014; Luck & Vogel, 2013; Nettelbeck & Burns, 2010). Ottley et al., (2013) found that performance differences were ascribed to the task type, whereby high-level task types relate to subjective and open ended decision-making activities, while low-level task types refer to retrieval, sorting and computing activities (Ottley, Crouser, Ziemkiewicz, & Chang, 2013). Cognitive factors including perceptual speed, visual working memory, verbal working memory and expertise suggest that further personalised support is required for the visual and domain non-expert decision-maker (Ottley et al., 2013). Users with lower measures of perceptual speed performed poorer than their higher measure counterparts and users with lower measures of verbal working memory performed poorer than their higher measure counterparts in sorting related tasks (Ottley et al., 2013). Participants with a low frequency of visualisation use spent considerably more time making their decision with horizontal visualisation layout than with vertical visualisation layout, with similar levels of subjective decision confidence and satisfaction (Ottley et al., 2013). In summary, user characteristics impact user performance on high-level decision-making tasks and visualisation layout should be further investigated for these tasks (Conati, Carenini, Hoque, Steichen, & Toker, 2014).

Literature relating to a human cognition framework for visualisation explained the relevance of data visualisation impact on cognition and perception in decision-making (Patterson et al., 2014). The study used different visualisation forms to aid decision-making and concluded that user preference of one visual form over another does not correlate with decision accuracy while cognitive processes are more important to maintain objectivity (Patterson et al., 2014). Further research into the use of images in information systems research noted that images inherently include knowledge that is relevant to the subject at hand and it is this knowledge that aids analysis, rather than the visual form itself (Andrade, Urquhart, & Arthanari, 2015).

Literature has identified the value of data visualisation to consolidate data by using cognitive principles to allow sense-making from vast amounts of data. Reference has been made to individual cognitive characteristics that affect decision-making efficacy. However; per the literature reviewed by the researcher, no clear guidance was provided in terms of what affects an executive's ability to consume data to aid in his/her strategic decision-making process, or what impact data visualisation has on his/her decision-making effectiveness. This leads to research question two.

RQ2: How does data visualisation impact on an executive's ability to use and digest relevant information, including on his/her decision-making speed and confidence?

2.2.5 *Data visualisation design considerations*

Visual design is not focussed on creating ‘pretty pictures’, but is rather centred on providing information that has relevancy and purpose for the task at hand. If the data visual does not display relevant information, the visual output could lead to confusion, frustration and incomprehension (Li et al., 2016).

According to Travica (2014), information and understanding is generated based on internal brain processing, rather than as an output, and is impacted by the person’s prior knowledge and perspectives (Travica, 2014). Travica (2014) also stated that humans are conditioned and one person’s interpretation can differ from another’s, even if both are viewing the same concept (Travica, 2014). Therefore, when a data visual expert designs, develops and presents a visual to an audience, the designer must consider the recipient’s requirements, interests, needs and agenda (Lee, Riche, Isenberg, & Carpendale, 2015). Travica (2014) provides a solution by stating that describing data elements in detail is favourable, as this assists in preventing confusion/misunderstanding, identifying required data types and the manner of its display (Travica, 2014). The data visual expert must also uncover what data is available, or could be retrieved, and what the primary purpose of the visual is (Travica, 2014). Is the data visual aimed at exploratory activities including the formulation of knowledge, generative activities which allow for the creation of a deeper understanding of a situation or for evaluative activities which test hypotheses? (Travica, 2014). If the data visual expert does not have the relevant information required, he/she could collect and analyse a representative sample of data for learning purposes, observe behaviour related to the situation, ask key personnel for their input, create simulations to predict an outcome or imagine a scenario and what the result could look like (Travica, 2014). Another approach to visual design is by determining the visual output. This is based on iconicity, in other words, how realistic or abstract the representation is and the relationship with time (Li et al., 2016).

The role of the data visual viewer is significant, as individual differences can impact on visualisation task effectiveness, performance and user satisfaction (Ward et al., 2010). Gaze data was used as a method to obtain real-time user information, to investigate whether individual user characteristics impact gaze patterns during visualization processing (Toker et al., 2013). The findings of the gaze data study showed that high perceptual speed can positively impact task performance in terms of both accuracy, as well as task completion time (Toker et al., 2013). For instance, it was found that low perceptual speed users tended to access a visualization legend more than high perceptual speed users, suggesting that they should be specifically supported in terms of legend processing (Toker et al., 2013).

Do data visualisation design elements, such as colour, size and data grouping affect user performance? To test such a premise, an experiment was conducted whereby participants were asked to find a target within a visual (Gramazio, Schloss, & Laidlaw, 2014). Two experiments were conducted, one using a scatterplot and one depicting squares within a grid. A scatter plot displays variables plotted against axes in a graph, whereby potential correlations can be viewed (Baarz & Cowan, 2013). A grid allows multiple data to be displayed in a tabular format, creating the ability to sort, drill into or exclude data for decision-making (Farhangi, 2010). The results of the scatterplot and grid experiments concluded that colour layout, quantity and size of the marks impact on visual search time, impacting user performance (Gramazio et al., 2014; Ware, 2012). Guidelines to enhance optimal visualisation design were identified, namely grouping similar marks and colours together. Secondly, spatial ordering of marks in relation to the number and size of visual marks also impacts user performance (Gramazio et al., 2014). A visual memorability study determined design aspects that make a visual memorable (Borkin et al., 2013). The results identified that the use of colour and human recognisable objects increases visual memorability. Travica (2014) also specifies that in order to create an effective data visualisation, the presenter must use recognisable objects that mirror the world view as closely as possible (Travica, 2014). For example, a vehicle dashboard is often used for data visualisations, as viewers are familiar with the interpretation of the vehicle dashboard components and measuring tools, such as the speedometer and fuel indicator (Travica, 2014). In summary, a condensed view of the principles of effective graphics is identified in Figure 10.

Principle	Principle Explanation
The Proximity Compatibility Principle	More integrated tasks are facilitated by displays that are high in display proximity; more focused tasks are facilitated by displays that are low in display proximity.
The Relevance Principle of Graphics	Present no more or no less information than is needed by the user.
Principle of Capacity Limitations	Displays should be designed to take account of limitations in working memory and attention.
Apprehension Principle	A visual display has to be accurately perceived. Present animations at a speed that can be apprehended and use visual dimensions that are accurately judged.
Principle of Discriminability	Visual forms indicating a difference between two variables should differ by a large enough amount to be perceived as different.
Principle of Compatibility	A visual display is easier to understand if its form is compatible with its meaning.
Principle of Salience Principle of Informative Changes	Design displays to make the most important thematic information salient. Avoid large changes in properties of a display that do not carry information.
Principle of Appropriate Knowledge	Ensure that the viewer has the necessary knowledge to extract and interpret the information in the display.
Principle of Visual Momentum	Code multiple displays consistently and provide visual aids to help users make referential connections between different displays and avoid disorientation in animated and interactive displays.

Figure 10 Principles of Effective Graphics (Hegarty, 2011).

Design principles for data visualisations were also constructed on the design science research (DSR) methodology (Engelbrecht, Botha, & Alberts, 2015). The intended use of the data visualisation, the ability of the visual to zoom in and out, obtain details as required, identify data, retaining the actions of the user, extract sub-sets of information, translate user requirements and avail meta data must all be considered in data visualisation design (Engelbrecht et al., 2015; Kimball, 2013). However, the design principles were limited to development within design science research, but had no practical reference, such as being tested on a sample of people.

What about other qualitative factors such as the data visualisation presenter's education and experience, the decision-maker's standing within the organisation and corporate culture? Do they impact on data visualisations use? A study of evidence based management (EBM) which uses reasonability and logic as a basis for decision-making, concluded that the organisational context, as well as the decision-maker themselves, enables EBM (Wright et al., 2015). Thus, it can also be argued that because data visualisation is used by humans as an enabling tool for improving the decision-making process (Gatto, 2015); one cannot completely separate data visualisation from qualitative/intangible decision-making influences. However, literature does not satisfactorily explain how and what qualitative factors of both the data visualisation presenter and data visualisation viewer should be considered in data visualisation design.

Literature has identified the importance of data visualisation design considerations such as the impact of colour, size and symbolic references. Literature has also identified design principles to produce more effective graphics. However; per the literature reviewed by the researcher, no clear guidance was provided in terms of other factors which could impact on an executive's desire to use data visualisations, such as presentation method or approach, technological awareness or the effect of corporate culture. This leads to research question three.

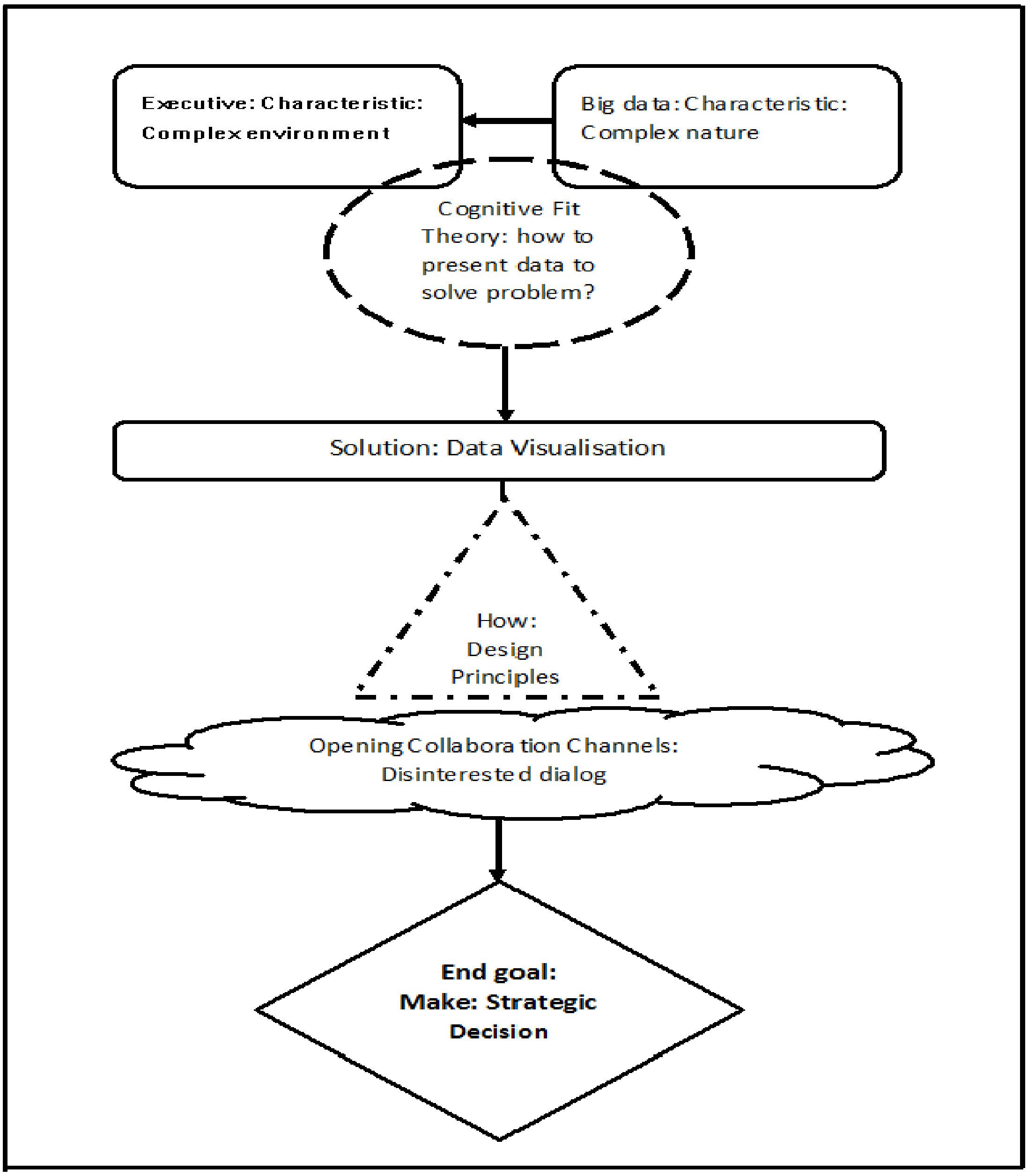
RQ3: What elements should data analysts consider when developing data visualisations?

2.3 Conceptual Model

Based on the literature review performed, the researcher created a conceptual model, documented in Figure 11. Figure 11 commences with the executive, the key role player in this study, who is accountable, responsible and therefore must be appropriately equipped to make informed strategic decisions. According to Shepherd and Rudd (2014), executives are impacted by 4 variables which affect their strategic making process (Shepherd & Rudd, 2014). These include internal and external organisational influences, such as internal performance and structure, as well as external uncertainties and instabilities, the styles and personalities of the executive or team and finally, the motive and pressure behind the strategic decision (Shepherd & Rudd, 2014). Therefore, the executive is facing complexity, which must somehow be unpacked to answer questions relating to the business problem in varying contexts, leading to an actionable decision (McLeod & Childs, 2013). Leading from this complexity, the Cynefin framework identifies the complex domain as an area in which the executive must probe to find the answers, as the cause and effect of the decision is unknown (Snowden, 2002). Only after the investigation has been performed and a sense of the situation attained, can the executive act upon his/her understanding (Czinki & Hentschel, 2016).

The second area of consideration in Figure 11 is big data. According to McAfee et al., (2012), big data correlates itself with large volumes, increased velocity and variety (McAfee et al., 2012). However, big data has also created increased concern regarding its value and veracity, adding to the complexity in which data is not only acquired but how data benefit is derived (Tamhane & Sayyad, 2015). According to Mandinach et al., (2006), data driven decision making is widely used as a framework supporting the ability to evolve raw data, to information, and finally into knowledge that can be effectively used for decision-making using cognition to collect, organise, analyse, summarise, synthesize and prioritise data for effective use (Mandinach & Jackson, 2012).

Finally, the executive then engages in a process of disinterested dialogue, whereby he/she consults and engages with his/her peers and subject matter experts, together with the quantitative data collected during the data driven process (Garbuio et al., 2015). Once all data, both quantitative and qualitative, has been collected, the executive can make the final strategic decision. However, the manner in which the data is presented impacts on the ability of the executive to consume the data for effective strategic decision-making, thus data visualisation must conform to design principles that match the mental model of the visual viewer (Hegarty, 2011; John & Kundisch, 2015).



Visualisation of Data to Optimise Strategic Decision-making

Figure 11 Researcher's Conceptual Model of Data Visualisation Use in Strategic Decision-Making.

While research has been performed regarding the elements of good visualisation design and its success within the realm of big data for sense-making, little research has been performed in understanding the use of data visualisation to optimise the executive strategic decision-making process predominantly from the perspective of executives.

RQ1: What do individual organisational executives value and use in data and data visualisation for strategic decision-making purposes?

Executives are operating in complex environments and making decisions where the cause and effect are largely unknown (Snowden, 2002). Executives rely on internal and external data, as well as their individual judgement, to make strategic decisions (Steiner, 2010). It is not only the use of quantitative data but also qualitative data that is meaningful to the process of strategic decision-making (Garbuio et al., 2015). Data driven decision making is widely used as a framework supporting the ability to evolve raw data, into information, and finally into knowledge that can be effectively used for decision-making. This is achieved through six cognitive processes: collecting, organising, analysing, summarising, synthesizing and prioritising (Mandinach et al., 2006).

Although it has been identified in the literature review that data remains a key criterion in strategic decision-making, further research is required to understand what executives value in data when making strategic decisions, which will identify the type of data considered critical for such decisions.

RQ2: How does data visualisation impact on an executive's ability to use and digest relevant information, including on his/her decision-making speed and confidence?

Data visualisation has been widely used within organisations to assist with sense-making of large volumes of data from varied sources (Toker et al., 2013). Data visualisation use is widely applauded due to its ability to use the human visual system to assist in gap recognition, pattern identification and intuitive interpretation when used correctly and effectively. It's significantly linked to the cognitive functioning of individuals (Wang, 2015).

Another important aspect to consider is the element of trust, encompassing the reliability, timeliness and accuracy of data used (Sun et al., 2012). Considerations leading to data mistrust include discrepancies between the data source and data store, discrepancies in calculations, differing data definitions and non-adaptive data infrastructure to support the needs of the end-user (Marshall & De la Harpe, 2009).

Further research is required to understand whether executives truly identify with and relate to documented literature on using data visualisation as a valuable tool, assisting in strategic decision-making. This will assist in identifying factors that can determine the success or failure of a data visualisation.

RQ3: What elements should data analysts consider when developing data visualisations?

Literature supports the idea that data visualisation should not be about the creation of ‘pretty pictures’, but images that invoke sense-making by displaying identifiable images in constructive ways that mimic the mental model of the decision-maker (Li et al., 2016). The data visualisation medium must ‘fit’ the data being displayed and link to the problem-solving task to allow for intuitive and rapid interpretation (Teets et al., 2010).

Other qualitative factors affecting the use of data visualisation in strategic decision-making, such as the impact of corporate culture or the data visualisation presenter’s education or experience were not substantially identified within the literature. Further research is required to determine if executives are impacted by such factors when making strategic decisions, which data visualisation may or may not be able to circumvent.

3 RESEARCH APPROACH

Qualitative research can be described as using words rather than precise measurements or calculations when performing data collection and analysis and uses methods of observation, human experiences and inquiry to explain the results of a study (Bryman, 2015; Richards, 2014). Qualitative research methods are aimed at creating knowledge whereby further meaning and understanding can be derived relating to a subject area (Male, 2015; Myers & Newman, 2007). Qualitative research importance within the social science realm has increased, as there is a need to further understand the connection of the research study to people’s emotions, culture and experiences (Creswell, 2013; Lub, 2015; Nassaji, 2015).

Why is a qualitative methodology the most appropriate methodology for this research paper? To answer this question, one must refer back to the research objective and purpose. The research study is aimed at explaining what principles should be adopted to optimise strategic decision making. However, based on the researcher’s initial literature review, it was not evident as to what executives use and value in data visualisations to facilitate effective strategic decision-making. In order to identify these influences, the researcher must obtain and transcribe verbal insight from the sample of executives, with supporting information from data analysts, regarding their experiences, challenges, views and perceptions (Creswell, 2013; Lub, 2015). Such meaningful information cannot be shared in quantified results and the outer practitioner community is in hope that research initiatives can direct new insights for meaningful use (Silverman, 2016). Furthermore, the choice of the qualitative methodology is also directed by the views of the researcher which impacts on the data to be collected and analysed, the method of obtaining the data and the manner in which the data is to be presented by the researcher (Grbich, 2012). The researcher’s view is that technology proves ineffective if it cannot be efficiently used by the end-user, therefore understanding the views of the subject (executive with support from data analysts) is important (Cresswell, Bates, & Sheikh, 2013). As described previously, the data collected is experience/perception-based, constructed from individual knowledge to derive greater meaning and understanding (Male, 2015). Finally, the proposed output of this research study is to provide an explanatory model for effective data visualisation design, therefore the views of the respondents are significant to direct such an initiative. Furthermore, data visualisation effectiveness is correlated to the end-user requirements (Toker et al., 2013).

This research applies theories of differing disciplines including information systems, organisational management and the psychology of human cognitive behaviour. In this respect, the use of theories from differing disciplines can be classified as mixed methods (Archibald, Radil, Zhang, & Hanson, 2015). However; the research methodology remains qualitative (Bryman, 2015; Richards, 2014). The research subjects, executives and data analysts, will provide individual accounts regarding data, information technology, data visualisations and other influential factors that affect strategic decision-making. Therefore, their situational factors bear significance in this study.

3.1 Research method

This research documented individual executive and data analyst responses within their corporate environment, via semi-structured interviews (Brinkmann, 2014; Galletta, 2013). Semi-structured interviews allow for more efficient data flow, allowing a deeper understanding of a phenomenon by formulating questions that relate to the topic at hand, allowing the participant to reflect and provide additional information that could introduce new dimensions not previously considered (Brikci & Green, 2007; Galletta, 2013; Burgoon, Guerrero, & Floyd, 2016). Furthermore, by performing a semi-structured interview, additional sets of information came to light that may be missed or hidden when performing only survey and questionnaire methods, such as additional personal experiences, body language, the tone of voice and facial expressions (Knapp et al., 2013). According to literature on a non-generalised study of the "clarification, adequacy and responsiveness in semi-structured telephone and face-to-face interviews", it was identified that respondent talk was more evident in face-to-face interviews (Irvine, Drew, & Sainsbury, 2013). Within this study, the participant requested clarification of questions more in telephone interviews as opposed to face-to-face interviews, sufficiency of respondent responses was more commonly verified in telephone interviews and they tended to be shorter than those conducted face-to-face (Irvine, Drew, & Sainsbury, 2013). This study did not discredit telephonic interviews, which is further supported by another study which identified the ability to provide more honest responses (Trier-Bieniek, 2012). The study did emphasise the need to develop a relationship or rapport with the respondent before continuing with the questions and questions must be clear to prevent mental overload (Vrij, Hope, & Fisher, 2014). At the same time, it is important to prevent "one-word" respondent answers, allowing him/her to speak without unnecessary interruptions, and to probe the respondent preventing information exclusion, which may impact the research study if omitted (Bryman, 2015). Interview protocols were further supported by literature relating to conducting semi-structured interviews. According to Raworth, Sweetman, Narayan, Rowlands and Hopkins (2012), the right audience, audience consent, information confidentiality, topic clarification, venue suitability, recording all information, listening attentively and lack of interviewer judgment are paramount and can enhance the success on the interview (Raworth, Sweetman, Narayan, Rowlands, & Hopkins, 2012). Refer to Appendix 1 for the interview questions.

3.2 Research process

3.2.1 *Population*

The population for this research comprised of executives tasked with strategic decision-making within the private sector who use data in strategic decision-making, as well as data analysts, either internal permanent employees or external consultants, who are tasked with data visualisation creation. This population provided insights that are reflective of both data visualisation design (data analyst view) and consumption (executive view). The unit of analysis is data visualisation.

3.2.2 *Sample*

The sampling method adopted purposeful sampling aimed at focussing the sample to those who were knowledgeable and experienced with the research topic, had good communication skills and were available and willing to participate in the research study (Palinkas et al., 2015). Additionally, maximum variation was applied which incorporates differing variables that may have an impact on the answers (Seidman, 2013). To demonstrate this, the sample took into consideration the person's functional position, years in job position and industry type. Race and gender have not been considered due to ethical reasons, as sensitivity exists surrounding race and gender in South Africa (Daniels, 2016).

The number of participants chosen and interviewed was dependent on saturation (Brown, 2005). Once no new meaningful information was obtained, the researcher concluded that saturation had been reached and no further interviews were held (Silverman, 2016). The sample incorporated 17 participants, 4 data analysts and 13 executives. More executives were chosen based upon the significance of executive responses for this research study, as compared to data analyst responses.

Table 1 provides a summary of all participants in this research study, identifying the industry where the executive resides and the pseudonym given to the participant to maintain anonymity. The combined number of years of experience within the data domain exceeded 50 years.

No.	Organisation Type/Category	Current level	Pseudonym
1	Financial	CEO	Ben
2	Technology	CEO	Kate
3	Financial	CIO	Dan

No.	Organisation Type/Category	Current level	Pseudonym
4	IT Software	CFO	Pete
5	Financial	CIO	Sue
6	Bank	CIO	Harry
7	Education	CIO	Xola
8	Consulting	CEO	Cindy
9	Financial	CIO	George
10	IT Software	CEO	Sipho
11	IT Software	CEO	Mike
12	IT Software	GM	Julie
13	Technology	Head: Sales and Business Development	Enid
14	IT Software	Data Expert (Internal)	Seth
15	Bank	Business Intelligence Head Data Expert (Internal)	Mia
16	Consulting	Data Expert (External)	Logan
17	Consulting	Data Expert (External)	Cassiem

Table 1 Interview participant demographic.

All participants were sourced independently, with the assistance of the researcher's supervisor. All prospective participants were emailed, requesting their participation. All respondents were given the choice to engage or decline the interview request. The researcher ensured that an approved letter from UCT was provided with the interview request, including a brief background to the research study.

3.2.3 *Data collection*

Once the respondents had formally accepted participation, a test interview to test the effectiveness of the questions was performed (Bryman & Bell, 2015). The first executive respondent commented that the questions were comprehensive and well-rounded, but that two of the questions relating to the use of data visualisation in strategic decision-making could be merged. This respondent had experience as a Chief Executive Officer, Chief Financial Officer and Chief Operations Officer with a sound academic post graduate qualification highlighting his/her ability to constructively critique the questions (Palinkas et al., 2015). Once rectified, the revised questions were used as a set of guidelines in all subsequent interviews. With regard to the data analyst questions, a similar response was provided. However; no revision of the questions was required. This respondent is a data analyst consultant within a global organisation and has over a decade of statistical, mathematical, risk and financial analysis experience.

All respondents were assured that all data would be treated confidentially and that he/she would have an opportunity to view and correct the recorded/documented information (Gray, 2013). The researcher also queried whether each respondent remained comfortable to commence the interview and allowed him/her the opportunity to terminate the interview at any stage (Qu & Dumay, 2011). All responses were transcribed and assessed (Alvesson, 2010). The majority of the interviews took between 60 and 90 minutes.

In terms of the logistical arrangements, the researcher queried the most appropriate method in which to conduct the interview (Rowley, 2012). It was intended that all interviews were performed face-to-face. However; telephonic interviews were necessary due to the availability and location of the participant (Trier-Bieniek, 2012). Figure 12 identifies the semi-structured interview process followed by the researcher.

1. Identified relevant participants to interview through purposeful sampling.
2. Obtained contact information of participants:
    a. An initial email to participant describing the research topic and intent to request respondent participation.
    b. If no response by a participant, telephonically contacted the participant and directly confirmed whether he/she wishes (or does not wish) to partake in the research study.
3. Successful participant participation:
    a. Arranged suitable time as per respondent.
    b. Arranged suitable location/venue as per respondent.
    c. Submitted questions prior to the interview, if requested by respondent.
    d. Submitted consent form (Ethics) to the respondent.
4. Unsuccessful participant participation:
    a. Thanked the participant for his/her time in responding and terminated further contact.
5. Arrived prepared and on time at interview location (or via telephone if the participant was not available for face-to-face interview) and conducted the interview. Dressed appropriately for the audience (respondent).
6. Conducted the interview in accordance with the protocols of good interview techniques.
7. Manually transcribed the interview in a timely manner.
8. Sent transcribed interview back to the participant and requested confirmation for use by respondent.
9. Ended Interview process. Thanked the participant for his/her valued contribution.

Figure 12 Researcher Process for Conducting Semi-Structured Interviews.

3.2.4 *Interview recording*

Although audio recording is often preferred due to its ability to record actual words, the researcher felt more comfortable with the hand-written method, as it allowed for further concentration and conceptualising of ideas as the interview was conducted orally (Jacob & Furgerson, 2012). Manual transcription also allowed the researcher to assess whether follow-on questions were required. The researcher also ensured transcript accuracy by sending the responses to the participant for verification (Mero-Jaffe, 2011). Once the interview was completed, the researcher transcribed the responses into a Microsoft word document. Additionally, a memo was documented describing additional researcher thoughts and ideas stemming from the interview (Goodell, Stage, & Cooke, 2016). The memo also identified any verbal or non-verbal information, such as body language and facial expressions, which may allude to the emphasis of a particular point.

The venue of the interview, the technology used during the interview by either participant or researcher, the participant's attitude toward the research topic and the tone and mannerisms of the participant during the interview could impact interview productivity (Myers & Newman, 2007). Therefore, the incorporation of both direct and indirect interview data is important, as both have an impact on the research outcome (Myers & Newman, 2007). Mimicry was also used by the researcher as an indirect interview tool, for example, by dressing in a similar manner that mimicked the environment in which the participant operated (Chartrand & van Baaren, 2009).

3.2.5 *Data analysis*

Once the data was collected, commonalities, differences, patterns and relationships were identified through thematic analysis (Brikci & Green, 2007; Guest, MacQueen, & Namey, 2011; Vaismoradi et al., 2013). Thematic analysis aids in concept definition by identifying patterns from the documented content in a hierarchical manner until the most eminent theme is produced (Braun, Clarke, & Terry, 2014). A substantive approach was applied which included the capturing and interpreting of meanings derived from the data collected, focussing on the participant's feelings, experiences and perceptions (Ritchie et al., 2013).Thematic analysis correlates to the researcher's approach to analyse data through pattern and relationship recognition, describing a particular phenomenon and building themes that can be used in future data visualisation development (Braun et al., 2014). Thematic data analysis is a non-linear approach, commonly used within qualitative research studies, and provides the opportunity to formulate new data trends/ideas which may not have been previously explored (Vaismoradi et al., 2013). As defined by Braun and Clarke (2006), Figure 13 describes the thematic process followed by the researcher:

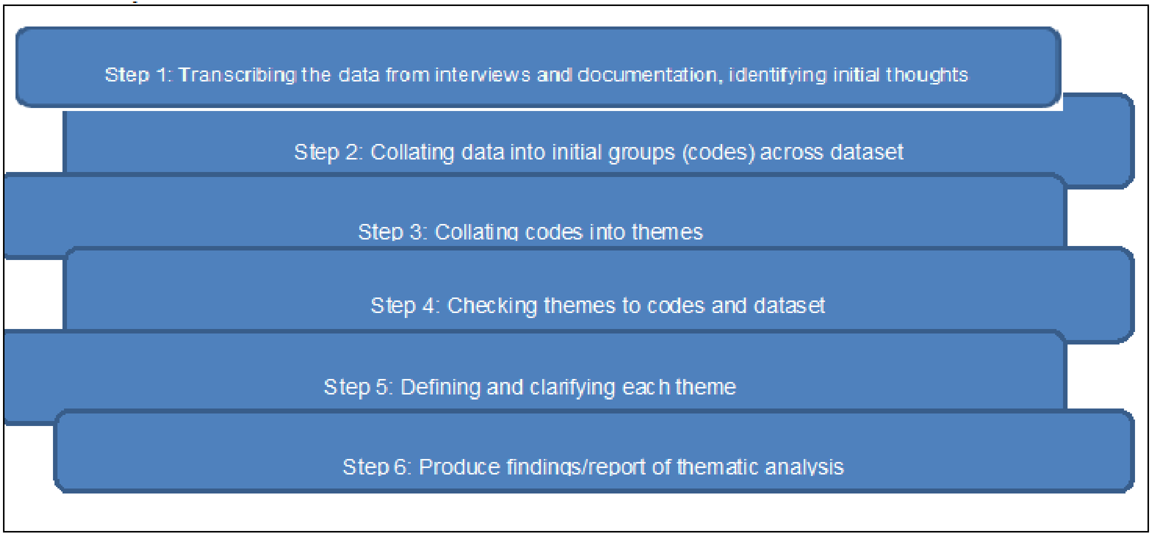


Figure 13 Thematic Data Analysis Process (Braun & Clarke, 2006).

The Nvivo qualitative data analysis tool supported the analysis of text data collected (Bazeley & Jackson, 2013). Nvivo 11 is a computer software package capable of analysing and organising rich text-based data in a meaningful and categorical manner (Hoover & Koerber, 2011). The benefits of using a qualitative data analysis software (QDAS) package, for example Nvivo 11, include the ability to store interview data and memoranda data in a central repository (Bergin, 2011). Nvivo 11 allowed the researcher to structure the data in a more user-friendly format and aided in the initial conceptualisation process, identifying preliminary patterns, significant participant responses and potential outliers (Woods, Paulus, Atkins, & Macklin, 2015). The researcher drove the data analysis process. However; the Nvivo tool facilitated faster analysis by providing grouping methods. This allowed the researcher to become immersed in the data, to initiate low-level coding, while reducing the time to seek such data patterns, trends and relationships (Vaismoradi et al., 2013). All analysis was performed solely by the researcher to avoid missing any ideas that may have resulted. Nvivo 11 also references the qualitative data analysis methods applied by Bazeley and Jackson (2013). Bazeley and Jackson (2013) identified the importance of understanding the research domain first, as this allows for contextualisation of participant responses (Silverman, 2013).

3.2.6 *Data validity and reliability*

Reliability was based upon evidence of research procedures upon which conclusions were drawn (Anfara et al., 2002). Validity refers to the precision of the research by determining how well the participants' responses and views have been captured and recorded (Ritchie et al., 2013).

Trustworthiness, which provides a basis for research relevancy, was achieved by collecting the most suitable data via critical reference groups (executives and data analysts) who will benefit from the research results (Elo et al., 2014). Triangulation was adopted by using differing data sources to check data validity (Hussein, 2015). In this research study, triangulation was achieved through the differing nature, composition and demographic of the individual. The researcher consistently adopted rigor in her data collection and analysis process (Thomas & Magilvy, 2011). The researcher has been involved within the IT risk advisory industry which includes, but is not limited to, the use of data. Prior practitioner experience has shown that the area of data visualisation has grown in importance and is considered a key instrument in decision-making practices (McCosker & Wilken, 2014). Furthermore, the interview questions were vetted by an executive practitioner within the data visualisation field. The purpose of this vetting process was to gain external confirmation that the interview questions would address the research objective (Lundstrom & Baker, 2009). The researcher also remained open-minded (Stelter, 2010). Responses to interview questions were emailed back to the participant, to authenticate and verify their accuracy (Ritchie et al., 2013). Data validity and reliability methods are documented in Figure 14.

Qualitative Characteristic	Strategy	Comments
Credibility	Prolonged engagement in field	Data collection commenced early in 2016 and continued into mid-2016.
	Peer Examination	Provided respondents with the views of their peers, verbally, without disclosing names or company/industry information.
	Triangulation	Collected data from several sources including interviews and then comparing the data by using corroboration with other data sources (Hussein, 2015).
	Member checks	The researcher provided each respondent with their responses for verification.
	Time sampling	Not used
Transferability	Provide thick description	Used direct quotations from respondents (Myers & Newman, 2007).
	Purposeful sampling	Sample selection of executives and data analysts, who are knowledgeable and experienced with the research topic and were also available and willing to participate in the research study (Palinkas et al., 2015).
Dependability	Audit trail	All interviews, consent forms, responses, and coding were maintained in a structured folder.
	Code-recode strategy	All data was open coded several times, and then axially coded, and finally selectively coded (Wolfswinkel, Furtmueller, & Wilderom, 2013).
	Peer examination	Provided respondents with the views of their peers without disclosing names or company/industry information.
	Triangulation	Collected data from several sources including interviews and then comparing the data by using corroboration with other data sources (Hussein, 2015).
Confirmability	Triangulation	Collected data from several sources including interviews and then comparing the data by using corroboration with other data sources (Hussein, 2015).
	Practice reflexivity	Used reflexive methodology throughout research by asking questions throughout study relating to research ethics, meaningfulness, advantages, usefulness and limitations (Alvesson & Sköldberg, 2009).

Figure 14 Quantitative and Qualitative Criteria for Assessing Research Quality and Rigor (Anfara et al., 2002).

3.2.7 *Ethics*

The researcher followed the prescribed University of Cape Town's (UCT) ethical process. The ethical process was conducted online. Permission was obtained from the researcher's Supervisor, the Information Systems ethics co-ordinator as well as the Ethics Committee Chair.

The consent form was signed by all respondents stating that no personal or company information would be published (Stahl et al., 2014). The respondent was also allowed to retract his/her responses at any time prior to, during or after the interview. Responses were transcribed and emailed back to the respondent for comment, allowing him/her to modify any information recorded (Mero-Jaffe, 2011). None of the respondents was dissatisfied with the recorded information, documented solely by the researcher. This indicated that the researcher had accurately interpreted and understood the participant.

3.3 Limitations

One significant limitation of the qualitative research methodology is its perceived lack of being scientific, as results are not quantifiable (Green & Thorogood, 2013). However, qualitative research is gaining momentum, support and importance in social science research, as there is a need to further understand the connection of the research study to people's emotions, culture and experiences (Lub, 2015). Furthermore, qualitative methods take subjectivity seriously and by implementing rigour during all stages of the research process, enhance the reliability of the results (Green & Thorogood, 2013).

In terms of the interview approach, a plausible limitation is that interviewees could state different views solely based upon being interviewed (Taylor, Bogdan, & DeVault, 2015). As the researcher used participants who were senior in the organisation, the freedom to express his/her views in a professional and open manner were greater than compared to lower levels of an organisation, as the fear of retribution is reduced. The research topic was also not politically motivated and the results thereof did not have a direct impact on the reputation or ability of the participant to fulfil his/her strategic requirements.

The researcher was also aware of the limitations of human based data analysis, including the tendency to exclude conflicting references, discount new insights, be deterred by first impressions and display judgement or bias (Bergin, 2011). To overcome such human limitations, the researcher again consciously included all responses, whether for or against the research topic, continuously revised participant responses and performed re-coding exercises (Woods et al., 2015). The researcher also used the research questions and Nvivo 11 to guide coding, preventing the researcher from becoming overwhelmed by the data collected (Zgraggen, Galakatos, Crotty, Fekete, & Kraska, 2016).

Finally, the researcher became aware of the limitations of using qualitative data analysis software, Nvivo 11. The researcher could become more focussed on the technical abilities of the software package, rather than focussing on the data meaning (Bergin, 2011; Cope, 2014). To prevent such data detachment, the researcher performed an initial assessment while transcribing the manually written notes per interview to Microsoft Word. This process allowed the researcher to immerse herself with the participant and interview data (Hoover & Koerber, 2011). This was the preliminary analysis (Grbich, 2012). Furthermore, the researcher was not experienced with research initiatives, including research methodologies, and hence was careful to follow formal research methodologies and elicit guidance from her supervisor throughout the study.

4 RESEARCH ANALYSIS METHOD

4.1 Analysis Method

The Nvivo qualitative analysis approach proposed by Bazeley and Jackson (2013) was used alongside the thematic analysis identified by Braun and Clarke (2006) to perform data preparation, data analysis coding, theme generation and findings formulation. The mapping between Braun and Clarke (2006) and Bazeley and Jackson (2013) is outlined in Figure 15.

Thematic Analysis (Braun & Clarke, 2006)	Nvivo Qualitative Analysis (Bazeley & Jackson, 2013)
1. Transcribing the data from interviews and documentation, identifying initial thoughts.	1. Data preparation and cleansing 2. Data import into Nvivo 11 (using word documents). 3. Initial data understanding using Nvivo query techniques 4. Memorandum (metadata) creation
2. Collating data into initial groups (codes) across dataset	5. Creation of child nodes
3. Collating codes into themes 4. Checking themes to codes and dataset 5. Defining and clarifying each theme	6. Grouping of nodes into parent nodes, also known as themes
6. Produce findings/report of thematic analysis	7. Transcription of themes into findings, advocated by existing literature

Figure 15 Mapping thematic analysis to Nvivo qualitative data methods.

4.1.1 *Transcribing the data from interviews and documentation, identifying initial thoughts*

4.1.1.1 Data preparation and cleansing

The researcher manually transcribed the interview, this was then recorded into a Microsoft Word document (McLellan, MacQueen, & Neidig, 2003). The main purpose was not only to have a central electronic copy of the interview, but provided the capability to upload data into Nvivo 11 (Hoover & Koerber, 2011).

With regards to the data verification process, eight executives responded that they did not want to see the transcripts for accuracy verification, as he/she was satisfied with the manner and flow in which the interview was conducted. Three executives responded via email that they were satisfied with the transcript accuracy and did not request any changes or additions. Two executives did not respond to the request for transcript verification. Based on the initial eleven satisfactory responses received, the researcher concluded that the remaining two transcripts were also satisfactory, as all transcripts were documented in the same manner. Two data analysts responded that they were satisfied with the transcript accuracy and did not request any changes or additions to the notes taken. Two data analysts did not respond to the request for transcript verification. Based on the initial two satisfactory responses received from the data analysts, the researcher concluded that the remaining two transcripts were also satisfactory, as all transcripts were documented in the same manner.

4.1.1.2 Data import into Nvivo 11 using word documents

The researcher manually highlighted the data per section and added it to a node in Nvivo 11 relating to the same question asked. A separate Nvivo 11 project was created for executive participant responses and data analyst responses. The purpose of this data cleansing step was to perform an initial categorical grouping of all data received during the data collection process, providing a starting point to assess the data and preventing any omission of interview data. Question responses were grouped to provide a view of data saturation per question. Participant responses were identified as key value points in order to identify any additional comments, concerns or suggestions relating to both the research topic and interview questions. The researcher completed this data preparation and cleansing step for all interview transcripts without adjusting the content or responses provided by the participant. The imported data was located in the Source domain of Nvivo 11. No other documentation was provided by the participants or imported into Nvivo 11, as it was confidential or not relevant to the participant responses.

4.1.1.3 Initial data understanding using Nvivo query techniques

The first data analysis step performed was to group participant responses per interview question. The purpose of this analysis was to identify points of saturation per question, to verify that no further interviews were required. The researcher manually copied the entire sentence or paragraph response into the relevant question or memorandum node, therefore sorting the entire Microsoft Word document into its initial constituent parts. Although it was a simple process to categorise the participant data into the relevant question and memorandum nodes, the Nvivo 11 tool did not provide a simple or concise visual representation to identify saturation points per question (Costa, de Souza, Moreira, de Souza, 2016; Cope, 2014). The Nvivo 11 tool was able to find generalised words within the same question for all interviews. However; the results of the similarities per word proved non-sensible to the researcher and hence a manual method of relationship identification using open and axial coding was performed (Wolfswinkel et al., 2013).

4.1.1.4 Memorandum data

Memorandum data, which identifies the thoughts and ideas of the researcher in relation to the topic or interview, were documented within nodes named “Meeting Logistics and Participant Behaviour” and “Executive responses to research study and topic and views of other research areas” (Bazeley & Jackson, 2013). The information captured in node “Meeting Logistics and Participant Behaviour” documented the researcher’s thoughts on the manner in which the interview was conducted for both data analysts and executives. The researcher concluded that the ability of the participant to engage openly and in dialogue or discussion form largely led to the success of the interview. For example, setting up the interview at a location and time suitable and comfortable to the participant allowed him/her to answer freely and provide valuable insights. The information captured in node *“Executive responses to research study and topic and views of other research areas”* documented information in relation to whether the executive liked or disliked the research topic, had concerns with the research or had potential future research initiatives leading from the research topic. This information was included in the data analysis located at sections 4.2 – 4.6.

4.1.2 *Collating data into initial groups (codes) across dataset*

4.1.2.1 Creation of child nodes

A process of coding, known as creating nodes in Nvivo 11, was adopted during the initial data analysis phase. This coding process considered the “surface features” of the data, providing an initial organisation of the data, thereafter categorising the data based on the type of occurrence being referenced (Hoover & Koerber, 2011). Finally, the data was grouped according to the similarities and differences identified within the data, which lead into further overarching concepts and themes (Gibbs, 2007). However, coding is also aimed at classifying data so that some form of ordered grouping is achieved. Therefore, the coding approach adopted was to be closely coupled to the data at the initial analysis stage, to grasp the narrative and essence or meaning of the data and what was being told (Braun and Clark, 2006). The researcher did not simply name or classify the data that was produced from the interview transcripts, but determined whether or not any patterns developed and identified the causes of the concepts and themes identified.

In summary, the approach adopted by the researcher to identify nodes included immersing themselves in the interview responses and applying judgement using the Lens Model proposed by Hastie and Dawes, (2010), linking common statements together (Gomez et al. 2012; Hastie & Dawes, 2010). Here, three key question categories were asked by the researcher whilst reviewing the interview responses. These question categories included relational understanding, impact and examination. Relational understanding means to use techniques to gain an overall understanding of something, someone, a situation or a phenomenon (Rico, Llabres, & Woo, 2015). Relational Understanding type questions attempt to have a broader, more holistic view in understanding an element in context with other related elements of the same problem, rather than only examining a specific element of the problem. Impact signifies the influence that could cause a change in the trajectory of something, someone, situation or phenomenon by having a positive, negative, or possibly neutral effect on that element (Kleis, Chwelos, Ramirez, & Cockburn, 2012). Verbs including “impact”, “determine”, “lead to”, “improve”, “influence”, “affect” and “make” all relate to the ability to portray a significant bearing on the interview response elements being compared. By definition, examine means to thoroughly inspect something, someone, a situation or phenomenon to determine its nature or condition (Wimble & Singh, 2015). In relation to this definition, questions asked relating to "examining", "investigating", "explaining", as well as time-related responses were grouped and defined as a node. By applying the thought processing stemming from relational understanding, impact and examination, the researcher was able to probe the interview responses in a deeper context, allowing commonalities to be more easily and methodically identified from the data (Jones, 2011).

An example of the results of the initial coding exercise are highlighted in Figure 16. Figure 16 identifies the main research question, the specific questions per research question, the participant to whom the question was asked, the name of the node as identified by the researcher and finally, the description of the node formulated based on the responses received per interview.

Main research question	Interview questions	Participant category	Nodes	Node Description
Q1: What do executives value and use in data for strategic decision-making?	Please refer to Appendix A, research question 1.	Executive	***General executive Thoughts on Data and Data Visualisation.**	This node details executive views regarding data, and data visualisation, whether positive or negative. This could allude to attitudes and factors enabling data visualisation acceptance, use and value.
			Human executive considerations affecting DV use, trust and data consumption.	This node represents personal factors of executives that may impact on his/her data consumption, data visualisation use and trust. This could allude to attitudes and factors leading to or against data visualisation use.
			Executive data governance concerns.	This node identifies data concerns that were provided by executives during the interview of which the researcher did not initially consider. It may allude to executive attitudes and factors that affect value and use of data.
			Missing data in executive strategic decisions.	This node identifies what executives consider is missing from a data perspective when making strategic decisions. This could allude to identifying data that is significant in strategic decision making, which should be included in data visualisation.
			Drivers of data visualisation	This node provides information regarding who typically drives data visualisation initiatives and why. This could allude to attitudes and factors of executives regarding data trust and control issues.
			Executive strategic decision making process	This node provides detail relating to the manner and ways in which the sampled executive group makes strategic decisions.

Figure 16 Initial data coding.

The researcher then performed a manual cognitive mapping exercise outside of Nvivo 11, as the researcher did not find a suitable way of depicting a large volume of data concisely in a graphical format that was easy to view and interpret within the Nvivo 11 tool. The researcher performed this manually on A3 sized paper. The purpose of the cognitive map was to visually represent data into concepts and ideas from a core word or idea (Burgess-Allen & Owen-Smith, 2010). The benefit of using cognitive maps is that it visually represents the natural thought processes, which are non-linear, and is also similar to the manner in which codes and categories are defined in qualitative data analysis software (Hou, Rashid, & Lee, 2017). Each participant response, whether it be from the executive or data analyst was linked to a specific node during the manual cognitive mapping process, based on linking the concept of the response to the node concept, as defined in the node description. Therefore, it was possible that a specific node did not necessarily relate to a specific interview question. The responses that were provided by the executives and data analysts were posed as questions back to the researcher and therefore each response was transcribed as a question. This demonstrated that the participants adopted a questioning and inquiring ethos, which directly corresponds to the collaborative and questioning requirement of data visualisations (Li et al., 2016). Figure 17 provides an example based on RQ1 (bubble A), which documents the node description (bubble B) and participant responses, in question form (textbox C), linked to child and parent themes documented at the end of each question. Child themes in this example include value, confidence and speed, while the parent theme is use. Based upon nuances identified per individual response, the researcher documented these nuances through sequential numbering. For example, Figure 17 textbox C identifies “(1.1.1 in excel)”. Therefore, this question has an additional element from subsequent interviews to the initial response received and documented, which was highlighted for the researcher’s data analysis process.

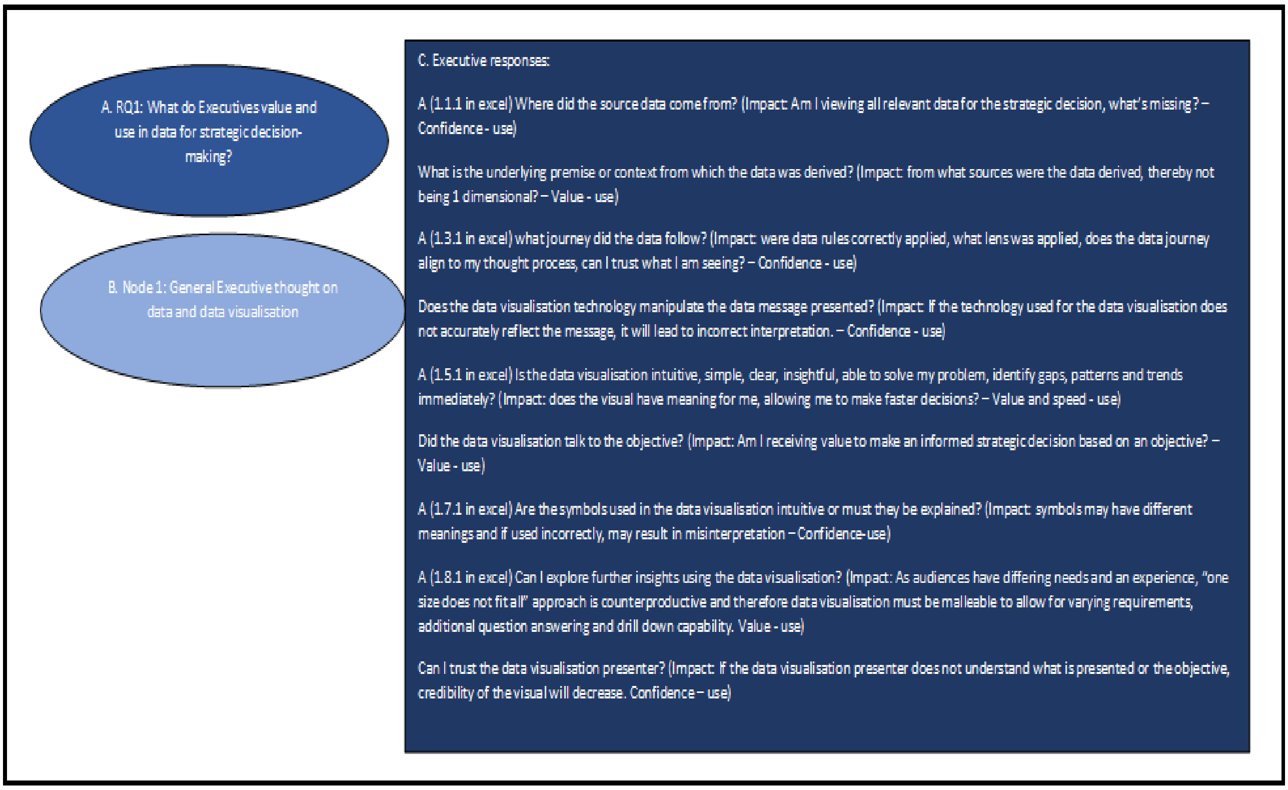


Figure 17 Research question, node, question and theme categorisation example.

4.1.3 *Collating codes into themes, checking themes to codes and dataset and defining and clarifying each theme*

4.1.3.1 Grouping of nodes into parent nodes, also known as themes

The process of defining themes was performed according to the thematic data analysis process described by Braun & Clarke (2006) in Figure 13. The theme construction process used included a reiterative process of collating codes into themes, ensuring that the refined themes align to the research question objective, while continually checking themes back to codes to ensure logical alignment and finally, defining and clarifying each theme. All data was open coded several times, by reading through the data several times and grouping related data based on the responses of participants, and then axially coded by identifying the relationship(s) between the open codes (Wolfswinkel et al., 2013).

The researcher again followed the approach of Gomez et al. (2012) to progress from the node definition to individual themes. The reason for the continuance of this approach was to align the approaches for node and theme definition as succinctly as possible, and to use holism, potential influence and inspection to align the nodes to determine themes, as well as to support the interviewee response method of responding with a question. (Rico et al., 2015; Kleis et al., 2012; Wimble & Singh, 2015).

Figure 18 depicts an example of the open and axial coding process performed by the researcher.

Participant Type	Research question	Node number	Node name	Node detail number	Node detail question (derived from responses)	Node Impact description	Final node data visualisation impact
Executive	RQ1: What do executives value and use in data for strategic decision-making?	1	General Executive thought on data and data visualisation	1.1.1	Where did the source data come from?	Am I viewing all relevant data for the strategic decision, what's missing?	Confidence - use
Executive	RQ1: What do executives value and use in data for strategic decision-making?	1	General Executive thought on data and data visualisation	1.2	What is the underlying premise or context from which the data was derived?	From what sources were the data derived, thereby not being 1 dimensional?	Value - use

Figure 18 Example of the open and axial coding process.

Based upon the lack of concise visualisations within the Nvivo 11 qualitative data analysis software, the researcher reverted to Microsoft Excel. Microsoft Excel records data in tabular format and has limited graphical visualisation capabilities and data filtering techniques that allow for the researcher to engage with the dataset and easily apply filters that enable more granular data analysis. Once the participant responses were transcribed into the excel spreadsheet, the researcher determined the impact of each response posed by the participant. An impact is a judgemental measurement of the effect of an event on a particular situation, whether positive or negative (Pizzini, Lin, & Ziegenfuss, 2014). By defining the impact of each participant response, the researcher was able to consider the final outcome of each response. Once the impact was identified, the researcher was able to identify the themes. For example, in table 10, the response of the executive participant, *"Where did the source data come from?"* was recorded in relation to research question 1. By asking the question in the negative, i.e. in relation to the lack of source data, the impact was identified *"Am I viewing all relevant data for the strategic decision? What is missing?"* This impacted on the executive's level of confidence since if he/she does not have all relevant and complete information, the executive may not be able to make an informed decision, and therefore will not be able to use the data visualisation effectively.

5 FINDINGS/REPORT OF THEMATIC ANALYSIS

5.1 Transcription of themes into findings, advocated by existing literature

In response to the three research questions, the emphasis was placed on the action words of the research question. In research question one, the emphasis was placed on *value* and *use* of data in strategic decision making, research question 2 refers again to *use*, but also to the *consumption* of data and decision-making *speed* and *confidence*, while research question 3 focussed on intangible elements which impact on data visualisation *use* for executive strategic decision making.

As a result of the impact assessment performed by the researcher of the executive and data analyst responses, the researcher was able to identify themes relating to *value, use, consumption, speed, meaning, trust* and *confidence*.

In order to understand the results leading to each theme, a definition of each has been documented below.

5.1.1 Consumption

Consumption occurs when items are used whilst engaging in a particular practice (Halkier et al., 2011). To be a proficient consumer, one must be able to acquire the services rendered, possess the tools allowing consumption to occur and finally, the practitioner must be attentive to the practice itself (Warde, 2005).

5.1.2 Speed

Speed is defined as perceptual speed, the ability of an individual to compare quickly and accurately, to recognise and absorb information such as patterns, numbers, letters, objects and pictures (Zsambok & Klein, 2014). Perceptual speed is important, as it allows the individual to identify errors quickly within time pressured environments (Ottley et al., 2013).

5.1.3 Confidence

Confidence is the ability of an individual to place belief or faith in something and to rely on it, displaying positivity in his/her judgement and expertise (Doozandeh, 2016). Confidence in decision-making is impacted by the perceived value of the decision and the efficacy of the assessment method to reach the decision, the accuracy of the information or evidence used to make the decision and the trustworthiness of the decision outcome (Graydon & Holloway, 2017).

5.1.4 Trust

Trust theory supports the notion that the decision to place trust in something is driven by a person's mental attitude, prediction or evaluation of the item, the intention to delegate trust, as well as the behaviour or intentional act of trusting (Castelfranchi & Falcone, 2010). Factors such as motivation, willingness, ability, "know-how", a person's self-confidence, beliefs, opportunities, dangers, obstacles and safety all impact on a person's decision to trust (Castelfranchi & Falcone, 2010). Regarding trust, reliability, timeliness and accuracy are also associated, impacting on a person's ability to make informed and accurate decisions (Sun et al., 2012).

5.1.5 Value

According to Grover and Kohli (2012), value, within the information technology environment, can be co-created amongst multiple stakeholders by sharing assets across the organisation, enabling knowledge sharing, as well as the capability to interact with other resources to create new data, products, services, processes and standards (Grover & Kohli, 2012). These elements are further controlled by governance structures that integrate the assets, knowledge sharing and complementary capabilities (Grover & Kohli, 2012). With the value definition presented by Grover and Kohli (2012), governance in the data visualisation realm relates to the appropriate use of data in terms of data capture, processing, storage and dissemination, as well as the controls surrounding data visualisation design and display, including the individuals allowed to view the data. As such, this governance construct links to the *use* definition.

5.1.6 Use

Use, within the information technology environment, is described through the technology acceptance model (TAM), which was developed for information technology adoption. It seeks to predict and explain IT usage behaviour and to determine what causes the rejection or adoption of information technology (Korpelainen & Kira, 2013). The TAM model has identified two constructs that impact on IT use, perceived usefulness and ease of use. Perceived usefulness refers to the degree to which the information technology improves an individual's performance in relation to the task at hand, while ease of use refers to the degree of effort required when using the information technology to complete a task. Both constructs are subjective and are reflective of an individual's feelings. In relation to the research topic, data visualisation seeks to improve the ability of individuals to simplify large volumes of complex data in order to consume it, interpret it and reach final decisions that can impact on the trajectory of the organisation.

5.1.7 Meaning

Although meaning was not specified as one of the child themes, it did connect with the value child theme though the assessment of the data visualisation presenter by asking whether the data visualisation presenter was able to guide the executive through the decision-making process. Meaning making is the ability of an individual to make sense of complexity and to apply significance or value to something (Stapleton & Wilson, 2017). Meaning can be impacted by an individual's past experiences (Graeupner & Coman, 2017).

Based on the evaluation of the impact leading to each theme, it was identified that a parent theme, *use*, was generated from each child theme, *speed, confidence, trust, value, meaning* and *consumption*. The parent theme directly relates to the research topic, as use, defined through the TAM model, affects the ability of an executive to engage and employ the data visualisation for his/her need and benefit to derive strategic decisions. Therefore, data visualisation use was identified as the outcome of the research topic. It was also identified that more than one child theme was coupled together to allow for use to be achieved.

5.2 Theme 1: Value

In relation to *value*, it was identified through participant responses that value, impacting the use outcome, was also linked to other child themes of confidence, speed, trust and meaning.

Figure 19 identifies the participant responses for value impacting on the *use* of data visualisation, the parent theme. Figure 19 highlights the primary child theme, value, and secondary child themes including confidence, trust, speed and meaning that arose during data analysis that linked to the primary child theme, value. The parent theme, for all tables, is use, as use (of data visualisation) serves as the core theme in this research study. Figure 19 also identifies the participant response in question form, linking it to a specific node defined in Nvivo 11 during the initial coding process. In instances where participant responses are italicised, for example, "Is the data visualisation intuitive, simple, clear, insightful, able to solve my problem, identify gaps, *implications*, patterns and trends immediately?" Such italicised words represent additional nuances or further responses linking to a pre-existing participant response. In this instance, a participant provided "*implications*" as an additional element to the response which had not been identified by other participant responses. This was also performed to ensure that all response data was documented without duplicating the core response.

Primary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Value	Use	What is the underlying premise or context from which the data was derived?	5
		How can I make my data visualisation impactful and easy to understand?	4
		Can I explore further insights using the data visualisation?	2
		Does the corporate culture nurture and accept an open, collaborative decision making process, focussing on individual strengths?	2
		How can I show different dimensions of data on the same data visualisation?	2
		What does the culture of the organisation look like? Do the executives have a collaborative style and do they understand the relevance and value of data for problem solving?	2
		Does the data visualisation support the executive's decision-making needs?	2
		Strategic decisions are specific in nature.	1
		The executive guides the direction and sets the objective of the data visualisation, not the data presenter.	1
		What is the context of the decision?	1

Primary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Value	Use	Do I understand the objective of what is to be achieved?	1
		What value will the strategic decision create?	1
		Does my organisation display strategic maturity to be able to use data visualisation effectively?	1
		Does the organisation have the capabilities to implement the strategic decision effectively?	1
		Do I understand the cause and effect of the strategic decision?	1
		Is the data visualisation appealing to look at and spark my interest?	1
		Can the data visualisation track the strategic journey and tell me whether or not the organisation is on track based on the decision made?	1
		Data visualisation is an on-going process, not once-off.	1
		Data visualisation training in the tool may or may not be beneficial, as executives have become more "tech savvy", but can improve overall data visualisation understanding.	1

Primary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Value	Use	Executives also like to play with the technology (data visualisation), to gain more confidence in it: "tried and tested approach".	1
		Is the technology used adaptable to different strategic scenarios?	1
		How data driven is my organisation and what is the nature of my business?	1
		How difficult is it to include qualitative data in data visualisation?	1
		Data visualisation for strategic decision-making may be too limiting, as not all organisations have a strategy.	1
		How can I incorporate changes into my data visualisation, and what impact will this have on the data?	1
		How much executive involvement do I need to produce a valuable, meaningful and successful data visualisation, using his/her insight and experience?	1
		How well can the executive articulate their requirements to me? Do they understand what they want?	1
		How can the executive compare their business to industry best practice?	1

Child Theme	Secondary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Value	Confidence	Use	Data visualisation is not largely used for strategic decision; more operational and historical data is presented.	1
Value	Trust	Use	How do I get the audience to understand and absorb what I am presenting easily?	2
Value	Speed	Use	Is the data visualisation intuitive, simple, clear, insightful, able to solve my problem, identify gaps, *implications*, patterns and trends immediately?	9
			Am I, *executive*, familiar with the topic at hand?	2
			Examples of strategic decisions made using data visualisation: implementing development operations, changing how operations and projects are split within the organisation and implemented, market segmentation, sales chasing, trends in software, client relationship strategy, increased human capital support within the business, business performance, product offering (true customer) and internal staff mentoring.	7
			Is the executive familiar with the technology used to develop the data visualisation?	1
Value	Meaning	Use	Is the presenter able to guide the executive through the data visualisation to reach a decision?	1

Figure 19 Summary of responses related to value theme.

Research question one is centred on *value* and *use* of data in strategic decision making. According to Grover and Kohli (2012), *value* of information technology enables knowledge sharing, as well as the capability to interact with other resources to create new data, products, services, processes and standards (Grover & Kohli, 2012). Perceived usefulness refers to the degree to which the information technology improves an individual's performance in relation to the task at hand, while ease of use refers to the degree of effort required when using the information technology to complete a task (Korpelainen & Kira, 2013). In relation to research question one; data visualisation is an information technology resource (asset) which enables knowledge sharing in a collaborative manner. Its use is reflected by how the data visualisation can enable effective strategic decision making in a manner that is intuitive. Based on the participant responses and data analysis performed, value and use were emphasised more in relation to data visualisation as the tool enabling value and use of data, rather than defining the value and use of data in isolation. This response correlates to the concept of data as described in the data driven decision making process by Mandinach, Honey, and Light (2006), whereby data is a raw constituent which has no meaning or value when contained in isolation (Mandinach et al., 2006). Furthermore, based on the data analysis performed, value on its own is not the only variable that leads to use but was also combined with confidence, trust, speed and meaning. The discussion below relates to the questions asked by executives, and data analysts, in order of the most responses to the least responses provided.

A fundamental question that was asked by executives in relation to data value was what is the underlying premise or context from which the data was derived? This response was identified under the value child theme in Figure 21, directly impacting on data visualisation use. Furthermore, this response identified the need for basic source data understanding in terms of the data used based on the proposition or background of the data analyst's understanding. The impact of this question directly influences decision accuracy. If the context or premise of the data source is incorrect, or one dimensional, the final decision may be misaligned and inaccurate. Additionally, the decision-making process focussing on only one segment of data creates the possibility of missed opportunities due to a siloed view. This response was supported by five executives including Pete, Sue, Harry, Sipho and Mike. Pete summarised this view succinctly by stating "*data should encompass broadness as opposed to depth to prevent one segment being missed or not considered in the strategic decision*". Pete also clearly stated that "*It is imperative to understand, or to have a better sense, of where the data is coming from and it is thus crucial to understand the data pipeline",* a view echoed by Sue who stated that "an extract of the source data is required to gain familiarity and context". The response regarding the underlying premise or context is partially supported by literature. Literature does identify data value as the ability to create competitive business advantage over an organisation's rivals (Tamhane & Sayyad, 2015; Tole, 2013), stresses the importance of deducing data relevant to the decision at hand (Mandinach et al., 2006; Weiner et al., 2015) and discusses how data collection is at the discretion of the decision-maker (Mandinach et al., 2006). However; literature does not adequately bring the importance of contextual and premise understanding within data visualisation presentation to the fore. Additionally, two data analysts, Seth and Mia, also raised questions in separate interviews relating to how they can show different data dimensions in the same data visualisation? This response aligns to the executives' concerns regarding siloed decision-making.

Another significant question which executives asked is whether the data visualisation is intuitive, simple, clear, insightful, able to solve his/her problem, identify gaps, implications, patterns and trends immediately? This response linked value to use through the speed child theme. The impact of this question, as deduced during coding, also influences *meaning* and *speed*, whereby such concepts allow the data visualisation to have significance for the viewer and facilitate faster decision-making. This response was asked nine times by five separate executives including Ben, Sipho, Mike, Julie and Enid. Julie summarised this the best by stating that *"It is someone who has a true business brain to really understand the value of data visualisation and that the whole point of data visualisation is to gather information and evoke a scenario to discuss and to uncover something else/new*". The concept of value leading to data visualisation use through speed is supported by literature which states that data visualisation must allow one to obtain insights, develop understanding and identify patterns, trends and anomalies faster to provide value for data visualisation use (Li et al., 2016). The literature also supports the concept of intuition, which relates to assembling and summarising various forms and amounts of data effectively for human interpretation (Campbell et al., 2015; Dasgupta et al., 2015; Gatto, 2015). The concepts of simplicity and clarity are also supported by literature which identified the importance of sense-making through extrapolating meaning from complex datasets (Reilly, 2014). The executive also adds to this question by referring data visualisation outward, to not only reviewing data within the data visualisation from an individualistic and internal perspective but also allowing further insights to be explored in an open and collaborative manner amongst peers. This response *"Can I explore further insights using the data visualisation?"* was identified by two executives, Sue and Harry. This response linked data visualisation value directly to its use. This implies that data visualisations must probe and initiate additional questions dynamically and collaboratively (Garbuio et al., 2015). Additionally, executives add to existing literature by specifying the need to identify and understand the implications of results quickly. Implications refer to conclusions that can be drawn from something (Acemoglu & Autor, 2011). From a data analyst perspective, the questions asked which support the need for value and trust of data visualisation, is how can he/she make his/her data visualisation impactful and easy to understand for the viewer, as well as how does he/she enable his/her audience to understand and absorb what he/she is presenting easily? These data analyst questions were asked by three separate data analysts, including Seth, Mia and Logan with a combined response count of 6. Sipho also responded with the need to understand the context of the decision, which impacts on the executive's ability to determine whether the data used was appropriate and aligned to the decision at hand.

Mia also raised a question on two separate occasions as to whether the data visualisation supports the executive's decision-making needs. The impact of this question, based on the coding performed, is if the need of the executive is not met, the data visualisation will not have the ability to align decision-making effort to an executive's requirement or objective. Literature does support the need concept, as the executive already has a preconceived idea of what the objective of the data visualisation is, and therefore the data visualisation output must meet this objective to be effective (Garbuio et al., 2015).

Another question posed by executives is whether the internal corporate culture nurtures and accepts an open, collaborative decision-making process, focussing on individual strengths to make informed, insightful and unified decisions. According to the data analysis performed, a lack of open communication amongst individuals stifles idea and solution generation which proves counterproductive to data visualisation goals. This question was asked by Ben and George. Although literature does support the concept of utilising the skills and knowledge of other executives in the strategic decision-making process (Garbuio et al., 2015), it does not specifically relate to the effect of the internal corporate culture on collaboration to enable open dialogue amongst executives in order to receive the knowledge and skills of others. Corporate culture is also a concern of data analysts, cited by Seth and Mia, who highlighted the importance of a collaborative organisational environment, as well as understanding the relevance of data value for problem-solving. A related concern, as identified by George, is whether the organisation displays enough strategic maturity to be able to use data visualisation effectively, while Sipho asked whether the organisation possesses the capabilities to implement the strategic decision once made. Enid asked whether the business nature and data driven-ness of the organisation is possibly the most influential factor affecting data visualisation use. The strategic management theory points to the strength of the decision-maker to be clear on the organisation's vision, mission, goals, internal processes and capabilities and external stimuli for effective strategic decision-making (Hill et al., 2014). Literature does however not define the impact of business nature on data visualisation value but does support the relevance of having a data driven culture within the organisation to obtain value from data for decision-making (Mandinach et al., 2006).

Another concept which has also been highlighted and which impacts on value and the resulting use of data visualisation is the executive's familiarity with the subject or topic at hand on which the decision is based. This response was posed by both an executive, Sipho and a data analyst, Mia. The impact of subject non-familiarity is if the executive is viewing the visualisation and the data for the first time, more explanation of how and why the data visualisation is constructed is required, and more effort on the part of the presenter is needed to impart the value of the data visualisation. The familiarity factor impacts on the speed child theme, linking data visualisation value to its use. This response supports existing literature which highlights the principle of appropriate knowledge which states that the viewer must have the necessary knowledge to extract and interpret the information in the display (Hegarty, 2011).

The discussion which follows identifies concepts for data visualisation value, and use that were raised independently. In other words, only one response was provided per participant which could be linked to a concept. One concept relates to the objective of the data visualisation. Dan cited that it is the executive who guides the direction and sets the objective of the data visualisation, not the data visualisation developer and/or presenter. Furthermore, George questioned whether the executive understands the objective and what needs to be achieved? These responses highlight that data visualisation is largely dependent on the executive's, or viewer's, vision at the point of initiation in order for the data visualisation to be perceived as valuable. By meeting the objective and aligning to the viewer's intention from the beginning, further buy-in is afforded, thereby reducing the need for a “hard-sell”. This observation is partly supported by the relevance principle of graphics which states that a graphic must present no more or no less information than is needed by the user (Hegarty, 2011), while the data driven decision-making framework identifies that the decision maker must decide what data to collect (Mandinach et al., 2006). Both literary points associate information relevancy with the user/decision-maker, which innately requires objective fulfilment, but does not point to the objective formalisation and the driver of the objective to enhance data visualisation value.

The technology used in the development and presentation of data visualisation was also linked to the value of data visualisation in terms of its flexibility and understand ability. In relation to flexibility, Cindy queried the adaptability of the data visualisation, as data visualisation can be a costly exercise and hence should incorporate changes as and when needed to support varying strategic scenarios. This sentiment was echoed by Seth, who stated that data analysts must identify how changes can be incorporated into the data visualisation and what impact those changes may have. The iterative nature of data visualisation is again supported by Kate who cited that data visualisation is an on-going process, sometimes yielding no finite end. This correlates to the process of strategic decision-making, as identified in the consumption child theme, under consumption - speed – use. In relation to understand ability, Sipho stated that he/she believed that upcoming executives are becoming more “tech savvy” and therefore training initiatives to enhance understanding may not always prove beneficial. Pete added to this “tech savvy-ness” by asking how “young” and “IT intelligent” are the executives in his/her organisation. Mike stated that in his/her experience, people like to familiarise themselves with technology to increase confidence, so that they may feel empowered to interact with the technology and presenter, as well as understand how the data visualisation is generated, including whether any data anomalies may occur based on the technology used. This opinion was also noted by Mia who also queried the executive’s familiarity with the technology used to develop the data visualisation as a core component of data visualisation value through the speed child theme. Data visualisation meaning, linking data visualisation value to its use, is enhanced through the ability of the presenter to guide the executive through the data visualisation to reach a decision. This observation was identified by George. However, if the executive has greater understanding of the technology used, then reliance on the presenter is diminished. Literature does support the cognitive fit theory whereby the problem-solving task and the problem-solving representation lead the decision-maker to solve the problem when both are aligned (Teets et al., 2010), as well as provide the ability of the decision-maker to use his/her reasoning to draw conclusions (Chang, Kao, Wu, & Su, 2016). However, literature does not specifically highlight technology understand ability or flexibility as a core benefactor for data visualisation value and use. An individual response from Enid asked whether the data visualisation will spark his/her interest and thus be appealing to look at. This response is attributed to the technology concept, as if the data visualisation is unappealing, it may cause the viewer to become disinterested and the resultant message may be lost. The technology aspect is also affected by its ability to include qualitative data such as motivation, as queried by Mike. Literature supports the relevancy of colour in data visualisation design by stating that colour does not only impact on aesthetics but can also improve visual search time and user performance, achieved through grouping similar colours together (Gramazio et al., 2014). Furthermore, the use of colour and human recognisable objects increases visual memorability (Borkin et al., 2013).

Responses specifically related to strategic decisions were also made. Enid stated that strategic decisions are specific in nature, identifying that one needs to first determine the value of the strategic decision, rather than the data visualisation itself. According to the impact analysis performed, if there is no value in the strategic decision itself, then there is no need to develop a data visualisation to assist in the decision-making process. George was concerned that data visualisation for strategic decision-making may be unachievable and limiting, as he/she has encountered organisations that do not have a strategy. Sipho believed that data visualisation is more relevant for presenting operational and historical data. This sentiment was however not shared by Pete, Sue, Cindy, George, Julie and Enid who provided examples where strategic decisions had been made through the use of data visualisation. Examples of strategic decisions included implementing development operations as a function of the business; redefining what a project and an operational task is thus streamlining workforce effort and impacting on long term productivity; understanding market segmentation for future product development and sales targeting; understanding clients to develop a long term customer relationship strategy; redefining human capital strategies within the business for improved workforce performance and staff mentoring and finally, understanding software trends for future product positioning. Literature does identify the benefit of using data as a means to support strategic decision-making, augmented through a data driven culture within the organisation (Mandinach et al., 2006; Rouhani et al., 2016). Strategic management theory relies upon internal and external organisational data to make informed decisions specifically aligned to the organisation's vision, mission and goals (Hill et al., 2014). Not only do executives rely on their skill and knowledge, but also those of their peers when making strategic decisions (Garbuio et al., 2015). Thus, there is a fundamental emphasis on data use for strategic decision-making, as well as ensuring that the strategic decision-making process is based on a solid intention. Other strategic decision related concerns included whether the executive truly understood the cause and effect of the strategic decision, as identified by George. Additionally, Sipho asked whether the data visualisation can track the strategic journey and tell him/her whether they remain "on track" based on the agreed decision taken, providing continual motivation for strategic implementation. According to literature, the Cynefin framework relevant to executive decision-making is embedded in the situational context of organisations, known as domains (Snowden, 2002). These situational contexts may be simple, complicated, chaotic, complex or disordered (Snowden & Boone, 2007). However, executives typically find themselves within the complex domain, where cause and effect are only understood upon reflection after the decision has been made and implemented (Czinki & Hentschel, 2016). In such circumstances, the executive is encouraged to experiment to find suitable answers through the use of data, dependent on the source is tacit or explicit to assist along the strategic journey (Gorzeń-Mitka & Okręglicka, 2014). Again, this emphasizes the need for data to assist in the strategic decision-making process.

Finally, Mia also provided a response relating to the value of data visualisation, leading to its use which included executive involvement in the data visualisation journey. Executive involvement in producing a valuable, meaningful and insightful data visualisation, whilst also identifying the value of the executive's skill and knowledge as a benefactor is important. Literature does support the need to use varying sources of information, including knowledgeable individuals, in the strategic decision-making process (Garbuio et al., 2015). However; literature does not point to the level of executive involvement in data visualisation development. For example, is this a continuous process or is involvement only at the initiation of the process to solidify the requirements? Based on the interviews performed, executives more often than not request to be involved at the initiation phase, such as Sue, whilst some prefer to be involved along the entire journey, such as Pete. Furthermore, how well an executive can articulate and describe his/her requirements also impacts on the data analyst's ability to align the data visualisation to the executive's objective. Literature does support the objective concept, as the data visualisation output must meet the executive's objective to be effective (Garbuio et al., 2015). Finally, there is also a need to find a plausible and unobtrusive way to incorporate industry best practice, to add meaning to the data visualisation. This observation is also noted for consumption – speed – value – use. Literature has identified the need for data visualisation to be intuitive, easy to use and understand, simple, accurate, insightful, to have integrity and be interactive (Campbell et al., 2015; Dasgupta et al., 2015; Khatri & Brown, 2010; Marshall & De la Harpe, 2009), but does not specify the inclusion of benchmark statistics to add to data visualisation value and use. In summary, data visualisation value is enhanced by being uncomplicated, collaborative, insightful and enabling problem solving that supports the executive's objective and decision-making needs.

5.3 Theme 2: Trust

In relation to *trust*, which is impacted by reliability, timeliness and accuracy (Sun et al., 2012), it was identified through participant responses that trust, impacting the use outcome, was also linked to other child themes of *confidence* and *consumption*. Confidence and consumption are also influenced by reliability, timeliness and accuracy (Graydon & Holloway, 2017; Warde, 2005).

Figure 20 identifies the participant responses for trust impacting on the *use* of data visualisation, the parent theme. Figure 20 highlights the primary child theme, trust, and secondary child themes including confidence and consumption that arose during data analysis that linked to the primary child theme, trust. The parent theme, for all tables is use, as use (of data visualisation) serves as the core theme in this research study. Figure 20 also identifies the participant response in question form, linking it to a specific node defined in Nvivo 11 during the initial coding process. Figure 20 also describes who provided the response (pseudonym) and the total number of times such a response was provided across all interviews held. In instances where participant responses are italicised, for example, "What journey did the data follow and why, /*what building blocks must I use to design the data visualisation*? such italicised words represent additional nuances or further responses linking to a pre-existing participant response. In this instance, a participant provided “*what building blocks must I use to design the data visualisation*” as an additional element to the response which had been identified by a data analyst as compared to an executive, relating to data visualisation design concepts. This was also performed to ensure that all response data was documented without duplicating the core response.

Primary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Trust	Use	Can I trust the data visualisation presenter?	2
		What journey did the data follow and why, /*What building blocks must I use to design the data visualisation*?	2
		How can I prove and disprove the hypotheses of the executive?	2
		How do I allow the executive to trust *and use* what I am presenting?	2
		Is the presenter faced with complexity such as multiple audience requirements, differing data domains and potentially difficult questions from a wider audience?	1
		What is the ranking of the presenter within the organisation?	1
		Is the presenter confident, knowledgeable in the data and visualisation objective, professional, uses good language, understands the data visualisation methodology used, shows maturity and is less defensive in his/her presentation and do they deliver the message correctly and accurately?	1
		Has the presenter been able to present a "wow factor", or something that is new and previously not known by the executive?	1

Child Theme	Secondary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Trust	Confidence	Use	Do I understand my business?	4
			What definition(s) have been applied to the data?	2
Trust	Consumption	Use	Does the conclusion drawn by the data visualisation presenter equate to my conclusion?	1

Figure 20 Summary of responses related to trust theme.

As per the data analysis performed, key questions posed by executives, including Ben and Enid, largely related to the data visualisation presenter, who may not only be the presenter of the data but could also be involved with the data visualisation development and design. On the other hand, Logan and Cassiem were posing the same question in relation to how they could allow the executive to trust, and hence use the data visualisation they present. The level of trust the executive has in the presenter is also associated with the ranking of the presenter in the organisation, as the participant, Ben, believes that a higher organisational ranking equates to higher knowledge of the business. Sipho identified the data visualisation presenter’s ability to handle complexity including multiple audience requirements, differing data domains and potential difficult questions posed by the audience, how confident, mature and professional the presenter is and how knowledgeable and understanding the presenter is in relation to the data visualisation objective and data visualisation methodology as criteria for presenter trust, directly impacting on data visualisation use. Furthermore, Sipho posed a question relating to the appropriateness of language used during the presentation and whether the presenter can deliver the message accurately and completely by stating *"data visualisation actually becomes more and more important if the message(s) conveyed are clear, crisp, impactful and meaningful".* Another variable affecting the trust of the executive in the data visualisation stemming from the presenter, and thus impacting on its use, is whether or not the data visualisation presented by the presenter has added value by identifying newness of which the executive was previously unaware. This observation was raised by Enid. Literature does not specify the presenter's intangible attributes or abilities, as identified by Ben, Sipho and Enid, to impact on trust and thus use of data visualisations.

From a data perspective, a key element to increase the trust of data visualisation, leading to use, is affording the executive the opportunity to also understand the data journey. This observation was raised by Pete. Such a question was also posed in relation to the confidence child theme, also directly impacting on data visualisation use. Confidence in decision-making is impacted by the perceived value of the decision and the efficacy of the assessment method to reach the decision, the accuracy of the information or evidence used to make the decision and the trustworthiness of the decision outcome (Graydon & Holloway, 2017). Confidence and trust are thus linked. Therefore, based on the definitions of confidence and trust, such a question in both themes clearly identifies the data journey as a core contributor to use in relation to trust and confidence. Furthermore, from the perspective of the data analyst, he/she is also concerned with the ability to demonstrate the building blocks used to design and construct the data visualisation, which includes the data journey. This question was raised by Cassiem. Literature supports the need to understand the data journey, including the confirmation of data accuracy as it progresses along the data pipeline (Marshall & De la Harpe, 2009). The impact of not understanding the data journey, as defined through the coding process, may result in incorrectly applied data rules, perspectives (also referred to as the lens), misaligned thought processing to solve a problem and distrust in what is being viewed on the data visualisation.

The need to prove or disprove a hypothesis, whether this is a problem statement or a question he/she has, was identified by Seth and Mia. The hypothesis test must not only prove their theory but also contribute to reasons why the initial hypothesis is null and void. The data analysts explained that the reason for disproving a hypothesis is to provide a more constructive and feasible approach to decision-making, whereby one needs to consider all possibilities, both positive and negative, even if it does not conform to an individual's initial understanding or requirement. Thus, disproving a hypothesis provides a more holistic perspective from which to base a decision. Literature does support the need to obtain all necessary data to make an informed decision (Hammond et al., 2015), as well as to prove and disprove hypotheses (Ward et al., 2010). Apart from the data analyst who raised this need, this concept was also identified by Harry, thus aligning the concern of the data analysts with the executive.

Considerations leading from trust, increasing the confidence child theme, and finally, data visualisation use were identified in relation to business understanding and data definitions. Firstly, executives placed significant emphasis on business understanding. As identified by Cindy, twice by George and Julie, if he/she does not have a true sense of the business and knowledge of the internal operations and strategy, as well as external influences on his/her business, this could reduce his/her confidence in decision-making, by identifying whether the data presented in the data visualisation is erroneous or incomplete.

Another important consideration as identified by Mike highlighted the importance of accurate data definitions. Mike mentioned that *"he will question what is being presented, including the definition of what is being presented"*. Executives realise that data may not conform to one definition throughout an organisation, especially within a distributed environment. Per executive responses, differing data definitions could result in inaccurate decisions, as different meanings may have different implications. Literature does support the need for consistency in data formatting affecting data understanding (Marshall & De la Harpe, 2009) and is also a metadata question which highlights the consistency in data definition within the data governance data decision domain framework (Khatri & Brown, 2010).

A final consideration leading from trust, increasing the consumption child theme, and finally, data visualisation use was identified in relation to the conclusion drawn during the data visualisation presentation. Pete stated that even if they did not draw the same conclusion as the data visualisation presenter, they were inclined to question rather than completely disuse the data visualisation. This response supports prior literature which has identified that data visualisation must create a platform for open and collaborative dialogue, as the viewer's conclusion alone may not always be correct (Garbuio et al., 2015). In summary, trust is largely associated with the data visualisation presenter, including his/her ability to produce a succinct message which the executive can understand and use, demonstrating that he/she clearly comprehends the executive's environment and the impact of internal and external influences in relation to the topic being discussed. The presenter must also display maturity and professionalism and be able to engage with multiple executives who may have differing objectives.

5.4 Theme 3: Consumption

In relation to *consumption*, it was identified through participant responses that consumption, impacting on the use outcome, was also linked to other child themes of *value* and *speed*.

Figure 21 identifies the participant responses for consumption impacting on the *use* of data visualisation, the parent theme. Figure 21 highlights the primary child theme, consumption and secondary child themes including value and speed. An additional third child theme was identified which joined speed and value, and could not be separated into the secondary child theme based on the participant response impact. The parent theme, for all tables, is use as use (of data visualisation) serves as the core theme in this research study. Figure 21 also identifies the participant response in question form, linking it to a specific node defined in Nvivo 11 during the initial coding process. Figure 21 also describes who provided the response (pseudonym) and the total number of times such a response was provided across all interviews held. In instances where participant responses are italicised, for example, "*Can I explore further insights using the data visualisation*? Does it support collaborative debate amongst my peers, *allowing collaboration amongst differing individual goals, thinking methodologies and techniques, insights and experiences and personalities*? Such italicised words represent additional nuances or further responses linking to a pre-existing participant response. In this instance, a participant provided "*can I explore further insights using the data visualisation*" and "*allowing collaboration amongst differing individual goals, thinking methodologies and techniques, insights and experiences and personalities"* as additional elements to the response which all linked to the concept of collaboration and insight generation. This was also performed to ensure that all response data was documented without duplicating the core response.

Primary Child Theme	**Parent Theme**	**Participant Response**	**Total number of participant responses**
Consumption	Use	*Can I explore further insights using the data visualisation?* Does it support collaborative debate amongst my peers, *allowing collaboration amongst differing individual goals, thinking methodologies and techniques, insights and experiences and personalities*?	4
		Does the data visualisation have "self-service" capability? Is it intuitive, easy to use, easy to understand, flexible, accurate, simple, predictive, enhanced, insightful and interactive and built on data integrity?	3
		Does the data visualisation translate into actionable steps *and answer "how"*?	2
		Am I allowed to have access to view and use this data? Do I understand how to use the data effectively and ethically?	2
		Does the data visualisation drive my own decision-making capabilities?	1
		Does the data visualisation fit the data presented?	1

Child Theme	Secondary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Consumption	Value	Use	Did the data visualisation talk to the objective?	7
Consumption	Speed	Use	Does the technology used in the data visualisation design enable seamless and intuitive thinking, *logical and hierarchical thinking processes, replicating the mental processes of the executive*?	5
			Am I familiar with the technology used to develop the data visualisation?	3
			Does the data visualisation support the iterative process of strategic decision-making for future prediction?	1

Child Theme	Secondary Child Theme	Third Child Theme	Parent Theme	Participant Response	Total number of participant responses
Consumption	Speed	Value	Use	Does the data visualisation support my data driven strategic decision-making process from start to end (problem research, top-down and bottom up approach, risk identification, collation of relevant data, data analysis, benchmarking, impact analysis?	1

Figure 191 Summary of responses related to consumption theme.

Research question two refers again to *use*, but also to the *consumption* of data and decision-making *speed* and *confidence.* Consumption of data refers to the intake of items during the act of engaging (Halkier et al., 2011). Based on the participant responses and data analysis performed, consumption on its own is not the only variable that leads to use but was also combined with *value* and *speed*. Speed, as a separately defined child theme, was identified to only be related to *use*, while confidence, as a separately defined child theme, was also linked to *value*, *speed* and *consumption*.

Based on participant responses, the following questions were asked to enhance *consumption* of data for executive strategic decision-making. Firstly, Ben, Harry, Sipho, Julie and Enid stated that to be able to consume the data in a data visualisation, he/she must be assured that the data visualisation talks to the objective or his/her requirement. Enid mentioned that *"she will be impressed if the tool used is good and that the technical person has shown that he/she understood the objective, is well illustrated without straining the brain to think"*. Based on the impact assessment performed, if the objective is not at the forefront of the data visualisation developer's mind, the potential for misinformed final decision increases, as the core reason for the development of the data visualisation is missed and the key question of the executive was not answered. This concept is supported by literature, as the data driven decision-making process requires the decision maker to answer a specific question that he/she has (Mandinach et al., 2006). This will then identify what data is relevant or irrelevant to the task at hand (Tole, 2013). Furthermore, the objective allows for a particular problem to be addressed, which guides the data collection process (Hammond et al., 2015). This concept of meeting an objective or requirement is also supported through the strategic management theory, which identifies the importance of first understanding the end goal in order to move forward in the strategic process (Hill et al., 2014). One data analyst, Logan, also identified the need to align clearly the data visualisation to the objective of the audience. Thus, the objective or requirement concept is supported by the data visualisation viewer and data visualisation developer and/or presenter.

Another significant question is whether the technology used in data visualisation design enables seamless and intuitive thinking as well as logical and hierarchical thinking processes, thus replicating the mental processes of the executive? This response was posed by Dan, Sipho and Enid. Adding to Dan's response, he was concerned that *"sometimes the 'why' is forgotten when using technology, as the emphasis may be too much on the technology and not the 'why' factor".* Based on the data analysis performed, the impact of not using the right technology in data visualisation design creates a distraction from the core message and hence the essence of the message is lost. According to Li et al., (2016), effective data visualisation design lessens the working memory of the viewer by creating deeper relationship understanding and grouping relevant information together (Li et al., 2016). Furthermore, cognitive fit theory, the theory related to information gathering and processing for problem-solving, identifies that the problem-solving task and the problem-solving representation creates a mental representation in the mind of the decision maker, leading the decision maker to solve the problem only when both are aligned (Teets et al., 2010). The ability of a data visualisation to be intuitive was also identified within the value child theme, which also impacted on speed and data visualisation use documented in Theme1: Value.

Another pertinent question posed by Cindy and Sipho was whether he/she is allowed to view and use the data within the data visualisation and whether he/she understands how to use the data effectively and ethically? Cindy added an additional outward-looking comment by stating that *"there is a need to delve into data access further and how the consumer can empower him/her-self from the insights the organisation is producing? This leads to questions surrounding ethical use of data. If the organisation is finding all this data about a particular customer, how is the consumer protected and able to access this data?"* The impact of a lack of data governance structures protecting acceptable data use relates to reputational damage of the organisation and potential legal action due to confidentiality and regulatory requirements (Weber et al., 2009). Data access has been identified as a key domain in the data governance framework developed by Khatri and Brown (2010) and one decision related to this domain identifies what data access standards and procedures are to be defined and implemented by the organisation

(Khatri & Brown, 2010). This data governance framework also identified that data quality must be established and communicated within the organisation, but does not specifically identify how ethical and effective data access will be communicated to executives and other stakeholders within the organisation. Data quality rather establishes data requirements and intended use in relation to data accuracy, timeliness, completeness and credibility (Khatri & Brown, 2010). However; it does not speak to the process of ethically and effectively using different data types in decision-making. Acts such as the Protection of Personal Information (POPI) provide guidance for collecting, processing, storing and sharing another entity's personal information, but this only relates to individual information, but not specifically to the principles and methods for data use in decision-making.

Executives also want data visualisation to enable further insight exploration; supporting debate amongst his/her peers, allowing collaboration amongst differing individual goals, thinking methodologies and techniques, insights, experiences and personalities. This concept was raised on four separate occasions by Sue, Enid and Logan. Based on the data analysis performed, the impact of a lack of collaboration increases the risk that the data visualisation does not support differing individual needs, requirements or goals to meet the overall objective of the data visualisation outcome (Garbuio et al., 2015; Toker et al., 2013). This collaborative effort was also identified as a benefit in further literature, as according to Nevo et al. (2015), Clayton (2013) and Krotov (2015), executives possess differing skills and are directed by varying sub strategies and oftentimes have differing organisational visions (Clayton, 2013; Krotov, 2015; Nevo et al., 2015). This means that a “one-size-fits-all” approach to data presentation is counterproductive and inhibiting (Nevo et al., 2015). Literature also supports the notion that executives rely not only on their judgement when making a strategic decision, but also refer to other executive skills and insight (Garbuio et al., 2015).

Additional questions which were posed by executives include whether or not he/she is familiar with the technology used to develop the data visualisation. The impact of technology unfamiliarity may prevent the message from being conveyed in an efficient manner by inadvertently creating a focus on the technology itself and its impact on the resultant outcome detracting from the core data message. Although the literature does support the cognitive fit theory whereby the problem-solving task and the problem-solving representation leads the decision maker to solve the problem when both are aligned (Teets et al., 2010), literature does not identify the lack of technology understanding as a key constraint in effective data visualisation use. The importance of technology familiarity was cited by Dan, Sipho and Enid. Another observation that linked to the ease of technology understanding included a response raised by George which stated: *“Does the data visualisation fit the data presented?”* Literature refers the principle of compatibility which states that the visual form must be compatible with its meaning (Hegarty, 2011). However, this principle speaks to the use of a metaphor or symbol that is commonly understood, rather than referring to aligning the data type to the best visual representation. For example, the principle of compatibility identifies a green smiley face with a positive outcome but does not specify that structured, unstructured, non-structured and semi-structured data must be presented in the form that is appropriate to its type (Kosslyn, 2006). The technology constraint was also identified in the value child theme documented in theme1: Value, whereby the value of data visualisation use is enhanced through the explorative capability of the technology.

Another key consideration, identified by Mike and Enid, is whether the data visualisation translates into actionable steps, answering *"how"* he/she can reach the decision outcome. Enid mentioned that *"if the data visual does not translate to actionable steps, such as decision-making, it will also be a failure."* The data visualisation life-cycle must exceed the point where the decision is made and continue to support the decision-maker after the decision is implemented. Furthermore, the iterative nature of the data visualisation to support future predictions, as noted by Enid, not only enhances speed leading to efficient data visualisation use, but also the ability of the data visualisation to support the holistic decision-making process. This additional observation relating to the holistic decision-making and support process was raised by George. George further stressed the importance of the data visualisation to provide research opportunity in relation to the problem statement or decision to support both top down and bottom up decision approaches, to have the ability to identify decision risk and impact, as well as consolidating data domains for analysis and including benchmarking statistics within the industry. Enid further added that data visualisation must also drive the executive's own decision-making capabilities. Enid stated that in her view, decision-makers want to remain in control of their decision-making, as they will ultimately be accountable for the decision outcome. Linking to the concept of continual decision support, a final observation was made by Cindy on two separate occasions as well as Logan. They stated that data visualisation must have "self-service" capability by being intuitive, easy to use and understand, flexible, accurate, simple, predictive, enhanced and insightful, possess interactive "drill-down" capability and be built on data integrity. Literature supports the intuitive, easy to use and understand, simple, accurate, insightful, integrity and interactive concepts (Campbell et al., 2015; Dasgupta et al., 2015; de Regt, 2014; Khatri & Brown, 2010; Marshall & De la Harpe, 2009), but does not specify the additional interactivity capabilities through visualisation drill-down capabilities to investigate problem statements and decisions further, or the ability of the data visualisation to be flexible on demand and support research opportunities, be enhanced to predict future trends and outcomes, support both top down and bottom up decision approaches, assist in decision risk and impact identification and provide benchmark statistics. Literature did, however, support the need to use the knowledge and skill of others when making strategic decisions, identifying the need to prevent a siloed and limited approach to decision-making (Garbuio et al., 2015) using only one segment of data. In summary, consumption is affected by data accuracy, integrity and quality, the technology used and by the ability of the data visualisation to support collaboration, whilst meeting the objective and requirements of the executive.

5.5 Theme 4: Speed

In relation to speed, it was identified through participant responses that speed was only linked to the use outcome. Speed has also been linked to child themes of consumption, confidence and value as secondary child themes. Figure 22 identifies the participant responses for speed impacting on the *use* of data visualisation, the parent theme. Figure 22 highlights the primary child theme, speed, and no secondary child themes. The parent theme, for all tables, is use as use (of data visualisation) serves as the core theme in this research study. Figure 22 also identifies the participant response in question form. Figure 22 also identifies the total number of times a response was provided across all interviews held. No additional nuances, as identified by italicised words, were highlighted for speed.

Theme 4: Speed – Use

Primary Child Theme	Parent Theme	Participant Response	Nvivo Node number(s) and name(s)	Total number of participant responses
Speed	Use	Does the data visualisation show contrast, such as colour (unobtrusive) or exceeded tolerance limits?	16 - Executive Data Visualisation Type_Form Preference	1

Figure 202 Summary of responses related to speed theme.

Only one core question was identified with regards to creating speed for executive strategic decisions. Other responses that related to speed were linked to value, *consumption and confidence* as secondary child themes, explained in theme1: Value, theme3: Consumption and theme5: Confidence. The core question related to speed asked by Julie was *"Does the data visualisation show contrast, such as colour (unobtrusive) or exceeded tolerance limits?"* The impact of having contrast increases the ability of the executive to find and solve problems faster, as anomalies are more easily identifiable. Literature supports this concept, as the results of an experiment which was aimed at defining what causes a visual to be memorable, identified that grouping colour similarity together increases faster search ability (Gramazio et al., 2014; Borkin et al., 2013). However, literature does not state the colour palette to use. As per Julie, softer tones are more pleasing to the eye that sharper and brighter colours, however, this is a matter of personal taste. Other contrasting factors identified through literature include differentiating between variables by using large distinguishing amounts known as the principle of discriminably. However, this principle was not cited by any executives or data analysts interviewed. Literature also does not state the relevance of tolerance limits for higher degrees of search ability. If a threshold is exceeded, such information should be presented at the forefront of the visual, for quicker problem identification. In summary, speed is enhanced through display characteristics, such as contrasting colours and bringing tolerance limit breaches to the fore in an identifiable manner for further analysis.

5.6 Theme 5: Confidence

In relation to confidence, it was identified through participant responses that confidence, impacting the use outcome, was also linked to other child themes of *value, speed* and *consumption*.

Figure 23 identifies the participant responses for confidence impacting on the *use* of data visualisation, the parent theme. Figure 23 highlights the primary child theme, confidence and secondary child themes including value speed and consumption, that arose during data analysis that linked to the primary child theme, trust. The parent theme, for all tables, is use as use (of data visualisation) serves as the core theme in this research study. Figure 23 also identifies the participant response in question form, linking it to a specific node defined in Nvivo 11 during the initial coding process. Figure 23 also describes the total number of times a response was provided across all interviews held. In instances where participant responses are italicised, for example, "Can I trust the data visualisation presenter *and does the presenter understand my business*?" Such italicised words represent additional nuances or further responses linking to a pre-existing participant response. In this instance, a participant provided "*and does the presenter understand my business*?*"* as an additional element to the response which all linked to the concept of the trustworthiness of the data visualisation presenter. This was also performed to ensure that all response data was documented without duplicating the core response.

Primary Child Theme	**Parent Theme**	**Participant Response**	**Total number of participant responses**
Confidence	Use	Can I trust the data visualisation presenter *and does the presenter understand my business*?	10
		Where did the source data come from *and how is it easily identifiable on the data visualisation*?	6
		Does the data support the actual decision? Is the data relevant/purposeful/robust?	6
		What journey did the data follow?	4
		Are the symbols, *and other representations*, used in the data visualisation intuitive or must they be explained?	3
		Does the data visualisation technology manipulate the data message presented?	2
		Is the source data accurate? Was the data mapped correctly between source systems?	2
		Can the executive trust the data visualisation presenter and does the presenter understand my business?	1
		Data quality increases confidence in using data within data visualisations.	1
		Do I have the time and IT skill/capability to design the data visualisation I want to?	1

Child Theme	Secondary Child Theme	Parent Theme	Participant Response	Total number of participant responses
Confidence	Value	Use	Does the data visualisation take me on a journey?	1
Confidence	Speed	Use	How relevant (timely) is the data I am using?	4
			What data, *or data elements*, is missing after reviewing available data?	2
			What type of data do I seek in strategic decision-making? Competitor, market related, culture-related, customer/client profile, external data, economy related data, human resources information and subjective data e.g. motivation.	2
			Do I understand my business? Does the data analyst understand their business?	2 1
Confidence	Consumption	Use	How can data *and data process quality, validity and* integrity be verified?	2
			How do I embed big data governance structures, when my traditional data governance structures lack maturity?	1
			Have I considered all data angles before making the strategic decision including: legal, financial, external market (industry) data, internal impact, cost of decision, customer experiences, customer product use, baseline, customer segmentation data, performance data, operational data, competitors in the industry, social data, customer reach and unique selling point factor?	1

Figure 213 Summary of responses related to confidence theme.

Based on participant responses, the following questions must be answered to allow for the *confidence* of data and data visualisation use for executive strategic decisions.

Firstly, as also identified within the trust theme, executives largely questioned their ability to trust the data visualisation presenter, who may not only be the presenter of the data but could also be involved with the data visualisation development and design. A key consideration allowing the executive to trust the data visualisation presenter is the presenter's ability to demonstrate an understanding of the organisation's internal business processes and external environment affecting the organisation. The relevance of business process understanding was echoed by both executives and data analysts including Ben, Kate, Cindy, Sipho, Mike, Julie, Seth, Mia and Logan on two separate occasions. Cindy mentioned that *"the participant answered that it's the person's experience not his/her education that matters. The person must understand the business processes and other processes which have a wider impact on the problem, not just his/her narrow view of the organisation".* The strategic management theory identifies the necessity of understanding internal strengths and weaknesses, as well as capitalising on external opportunities, whilst minimising exterior threats as essential steps in strategy formulation (Hill et al., 2014). However, existing literature does not highlight the necessity of the presenter's knowledge and skill as factors impacting confidence in data visualisation use. Per the impact assessment, if such organisational understanding is not demonstrated by the presenter, the credibility of the data visualisation diminishes, as the data presentation, insights and conclusion may be misaligned to the organisation's practices and requirements, proving unrealistic to the overall organisational (and executive) objective. Additionally, Dan and Julie also identified the necessity of the executive's understanding of the business environment in which they operate. This sentiment was also shared by Cindy and George on two separate occasions, as well as Julie under the trust theme, which linked use of data visualisation through the confidence child theme. Per the impact assessment, if the executive does not understand his/her business, data anomalies may not be quickly or easily identified, impacting on the speed of the decision formalisation. Data anomalies also impact on the effectiveness and accuracy of the decision. This conclusion is supported by literature which states that data visualisation must allow one to identify anomalies faster to be effective (Li et al., 2016).

Secondly, confidence of data visualisation use is increased if the executive is provided with an understanding of the origin of the source data, as well as being able to have a view of where the source data originated from, visible on the data visualisation itself. This was highlighted by both executives and data analysts, including Ben, George, Sipho on three separate occasions and Mia. Source data understanding impacts on data relevancy and assists the executive in identifying whether any data is missing or incomplete. Literature supports data relevancy by stressing the importance of not only having sufficient data available but also applicable information to make an informed decision (Hammond et al., 2015). Ben, Pete, Harry, Cindy, Mike and Julie also posed concepts relating to the purpose and robustness of data and whether the data presented supports the actual decision. Literature has also identified that data must support and meet the objective of the decision-making process (Mandinach et al., 2006). If not, superfluous data may impede the efficiency of the decision-making process (Engelbrecht et al., 2015). The importance of eliminating redundant data is further supported by the principles of effective graphics, including the relevance principle, which identifies that excessive, or limited, amounts of data must be avoided whilst taking into account the limitations of working memory and attention (Hegarty, 2011). Further emphasis was placed as to how the data source is presented. This provides a point of reference that is quick to identify, assisting the executive in determining any incomplete data points that may impact on his/her final decision. Data must also be displayed using intuitive and logical symbols that share a common meaning amongst more than one person, or should be explicitly explained as identified by Cindy and by Sipho on two separate occasions. This concept of common data symbolism understanding was supported by literary research which identified that objects which humans can recognise increases visual memorability (Borkin et al., 2013). Per the impact assessment performed, common data symbol understanding prevents misinterpretation. Literature supports the necessity of consistent data formats, as it eliminates the possibility of incorrect conclusions and distrust of the data (Marshall & De la Harpe, 2009).

Thirdly, as with the trust theme, executive confidence is also increased by providing an explanation of the data journey as highlighted by Sue on two separate occasions, as well as by Sipho and Mike. By understanding the data journey, the executive is able to determine whether or not the presenter applied the correct data rules, used the same (or different) lens and aligned thought processing to the executives. Source data accuracy is also a key concern for the executive, as this also impacts on the relevancy of data for strategic decision-making, while correctness of source data mapping between systems is another consideration of executives, including

Sue and Enid. Literature supports the need for checking data accuracy from the data source along the data journey (Marshall & De la Harpe, 2009; Sun et al., 2012), however, does not specifically state the relevance of data mapping within the data journey in data visualisation display. The framework for data decision domains as defined by Khatri and Brown (2010) does highlight data quality within data governance with one of the steps being standards applied to data accuracy and completeness (Khatri & Brown, 2010), but it does not specifically identify data mapping procedures from varying data sources as a key decision. Therefore, data mapping can be added as a question to the data visualisation metadata domain decisions.

Enid asked the question as to whether or not the data visualisation took him/her on a journey, which impacted on data visualisation through the value child theme. This extends from the source data observation, as the executive is further questioning the capability of the data visualisation to enable him/her to reach the decision outcome. Although literature does support the necessity of understanding the data journey as it progresses through the data visualisation development process (Marshall & De la Harpe, 2009), this is not taken from the view point of the executive who wishes to derive new insight and become aware of previously unknown concepts and ideas through a journey of understanding. Literature does support the concept of insight generation by defining data visualisation as a methodically developed graphic presenting data intuitively, enabling pattern and relationship formulation in an engaging manner (Li et al., 2016), but only sporadically points to methods of how to generate such insight by referring to the cognitive fit theory (Helfat & Peteraf, 2015) and understanding the problem-solving ability of the viewer (Li et al., 2016). A more formalised methodology for insight generation is not clearly defined in the literature. Per participant responses, insight generation can be sought through the value theme, which identifies the need to incorporate differing requirements of an audience, enabling the exploration of alternative decision outcomes in an open and collaborative environment and pre-empting additional questions which may, or may not be, at the forefront of the decision-maker's mind (Garbuio et al., 2015). Thus, the "one size fits all" ethos to data visualisation design is counterproductive. Therefore, data visualisation must be malleable to allow for varying individual requirements, additional question generation, as well as answering such questions, based on data that is readily available. Literature does support the need to take individual requirements into account, thus supporting the "one size does not fit all" concept (Nevo et al., 2015; Toker et al., 2013), as well as allowing individuals to engage in a collaborative manner (Garbuio et al., 2015). Furthermore, literature does support the big data value characteristic, which defines value as the use of data for competitive advantage, which is a greater possibility when insight generation is created (Bijker & Hart, 2013; Tamhane & Sayyad, 2015). However, the pre-emption of additional questions, via drill-down capability at the point when the question is asked is not clearly identified in the literature as a data visualisation value generating factor.

Fourthly, as with the consumption theme, executive familiarity with the technology used to develop the data visualisation is also important to increase executive confidence in data visualisation use as identified by Ben and Enid. The impact of technology unfamiliarity may create a feeling of distrust, as the executive may not have sufficient insight into how the technology affects or potentially could change the data or message displayed. Literature does not identify the lack of technology understanding as a constraint in effective data visualisation use and therefore, is considered a new insight into data visualisation development.

Cindy, George and Julie on two separate occasions questioned the timeliness of data used and presented in the data visualisation, which affects the executive's ability to not only become more confident in data visualisation use but also enhances the speed of decision-making. If data is untimely, it may lead to inaccurate and ineffective decisions thus reducing the ability to be competitively advantageous at that point in time. Literature does support the need for timely data in data governance discussions, within the data quality domain in the framework for data decision domains (Khatri & Brown, 2010). Furthermore, data timeliness also impacts on trustworthiness by assuring the data consumer that he/she is looking at the most relevant information at that point in time (Sun et al., 2012). Another timeliness statement raised by Harry was the time, and IT capability or skill, he/she has to design and develop a data visualisation. This statement is not clearly articulated in literature but has a bearing on the executive's involvement in data visualisation development, which per the impact assessment performed, could result in an effective or ineffective data visualisation. More time and IT skill allowed the executive the ability to explore and construct data visualisations.

Dan and Mike also questioned whether any data was missing after all available data at a point in time was viewed. This observation can also be linked to the source data observation, identified by Ben, George, Sipho and Mia in the discussion above, linking data visualisation confidence directly to its use. Source data understanding impacts on data relevancy and assists the executive in identifying whether any data is missing or incomplete (Hammond et al., 2015). Per the impact assessment, if relevant data to make a decision is unavailable, an executive may face uncertainty as he/she has less factual information to make a strategic decision. Uncertainty is a characteristic of strategic decisions, as defined in the strategic decision-making process by Shepherd and Rudd (2014). Therefore, to reduce the uncertainty coefficient, consideration on the part of the executive is needed to determine whether additional effort and investment is required to obtain the missing data, if available, or whether to forge ahead and make the decision using inner intuition (Garbuio et al., 2015; Shepherd & Rudd, 2014). Per the impact assessment performed, the type of data required for the strategic decision, as posed by Dan and Enid, also has a bearing on the certainty characteristic, as well as risk, as there is the possibility that executives may not be allowed to retrieve and use data based on ethical principles of acceptable data use. Such considerations are defined in data governance literature, largely driven by regulatory requirements (Khatri & Brown, 2010; Weber et al., 2009). Data types that Dan and George typically sought when making strategic decisions, which may not be available for use, included competitor, market-related, culture-related, customer/client profile, economic, human resources and subjective data. Pete added to this observation by stating that it is imperative to view all data angles and highlighted that legal, financial, internal organisational impact as a result of the decision, cost of decision and baseline, performance, customer experiences and product use, customer reach and unique selling point and social data are also valuable in strategic decision-making.

Finally, Dan and Mike on two separate occasions posed questions relating to data quality, validity and integrity and how they can be assured that these data principles have been included in data visualisation development. This has a direct impact on executive data consumption as per the data analysis performed. Such data themes are closely linked to data governance. Sipho further queried the data governance maturity of organisations, as he/she believed that today's organisations are still grappling with traditional data, as opposed to big data, governance structures. Per the impact assessment performed, the concept of "garbage in – garbage-out" was highlighted. As per discussion with the executives interviewed, he/she believed that if the data used is not valid and does not conform to quality and integrity standards, the final decision may be poorly constructed, uninformed, irrelevant and/or costly. Data governance, as highlighted in the literature, is a cornerstone for effective data use and decision-making (Fruehauf et al., 2015; Khatri & Brown, 2010; Weber et al., 2009). In summary, confidence is influenced by internal and external environment understanding by both presenter and viewer, data timeliness, data availability, data and data mapping accuracy, data integrity and quality, data origin and journey understanding, intuitive and common symbolism used and technology familiarity.

5.7 Summary

To summarise, in relation to RQ1, contributors to data and thus data visualisation value and use include identifying the value of the decision to the organisation first. If the decision does not have relevance in relation to the organisation's vision or goals, then the value of data visualisation and its use diminishes. Core questions relating to data premise, context and source understanding also impact on data, and thus data visualisation value. Data must be accurate and multi-dimensional to allow the executive the ability to view data from various angles and dimensions, creating a more succinct analysis. Data visualisation value is also enhanced by being uncomplicated, collaborative, insightful and enabling problem solving that supports the executive's objective and decision-making needs. Data visualisation must also identify anomalies, gaps and trends, whilst bringing the implications of decision alternatives to the fore. The data visualisation must also trace the decision from initiation to finalisation. Data visualisation value is also enhanced if the executive is skilled and knowledgeable in the data presented whilst operating in a data driven environment. Skill and knowledge also extend to technology understanding used in the data visualisation design journey and presentation method. If this skill and knowledge is not apparent, the presenter must guide the executive through the process to maintain value.

In relation to RQ2, contributors to consumption relate to some of the considerations identified in RQ1. For example, the objective set out by the executive must be achieved and the technology used to present the data must promote intuitive and seamless thinking, also enhancing logical and hierarchical thinking that follows the same mental model of the decision-maker. Consumption of data in data visualisation is also impacted by the ethics surrounding data use and data integrity measures, whilst supporting collaborative engagement amongst peers and explorative capability. Speed is enhanced through display characteristics, such as contrasting colours and bringing tolerance limit breaches to the fore in an identifiable manner. Results for RQ2 and RQ3 merged in terms of the confidence theme. In relation to RQ3, factors that should be considered in data visualisation design associated to confidence include internal and external environment understanding by both the presenter and viewer, data timeliness, data availability, data and data mapping accuracy, data integrity and quality, data origin and journey understanding, intuitive and common symbolism and technology familiarity.

Furthermore, RQ3 was influenced predominantly by the data visualisation presenter's organisational ranking, handling of audience diversity and complexity, ability to transfer the core message efficiently and effectively, ability to show professionalism and answer questions appropriately, display knowledge in the topic area under review and understanding the methodology or framework used to create the data visualisation. The data visualisation must also consider disproving hypotheses to show validity of the original hypothesis deduced by the executive and be consistent in data definitions used and conclusions drawn against the executive's assumptions.

6 CONCLUSION

The final section of this research paper, the conclusion, begins with a summary of the problem statement, research question and results, followed by a discussion of what can be learned from this research and finally, recommendations for optimising data visualisation use for executives.

6.1 Summary

The predominant problem encountered is that big data is produced at exponential rates and organisational executives may not possess the appropriate skill or knowledge to consume relevant big data for rigorous and timely strategic decision-making (Li et al., 2016; Marshall & De la Harpe, 2009; McNeely & Hahm, 2014).

6.1.1 *Sub-problems*

To reiterate, the sub-problems included that each executive category (Chief Executive Officers (CEOs), Chief Financial Officers (CFOs) and Chief Operating Officers (COOs)) possess unique and differing characteristics including education, IT skill, goals, experiences and operate within a corporate culture, which will impact on his/her ability to make rigorous and timely strategic decisions (Campbell et al., 2015; Clayton, 2013; Krotov, 2015; Montibeller & Winterfeldt, 2015). Furthermore, data visualisations are often not "fit-for-purpose", meaning that they do not consistently or adequately guide executive strategic decision-making for organisational success (Nevo et al., 2015). Data visualisation development currently faces challenges, including resolving the interaction between data and human intuition, as well as the incorporation of big data to derive competitive advantage (Goes, 2014; Moorthy et al., 2015; Teras & Raghunathan, 2015). Such challenges have directed the formulation of three research questions:

RQ1: What do individual organisational executives value and use in data and data visualisation for strategic decision-making purposes?

RQ2: How does data visualisation impact on an executive's ability to use and digest relevant information, including on his/her decision-making speed and confidence?

RQ3: What elements should data analysts consider when developing data visualisations?

Based upon the findings, to answer RQ1, organisational executives must first be clear on the value of the decision. No benefit will be derived from data visualisation if the decision lacks value. The executives also stressed the importance of understanding how data relevancy was identified, based on the premise used by the data visualisation developers. Executives also value source data accuracy and preventing a one-dimensional view by only incorporating data from one source. Hence the value of dynamism, or differing data angles, is important. In terms of the value in data visualisation, it must provide simplicity, clarity, intuitiveness, insightfulness, gap, pattern and trending capability in a collaboration enabling manner, supporting the requirements and decision objectives of the executive. However, an additional finding also identified the importance of the executive's knowledge of the topic at hand and having some familiarity of the topic. Finally, the presenter of the visualisation must also provide a guiding force to assist the executive in reaching a final decision, but not actually formulate the decision for the executive.

RQ2: How does data visualisation impact on an executive's ability to use and digest relevant information, including on his/her decision-making speed and confidence?

Based on the findings, to answer RQ2, themes of consumption, speed and confidence can be used. However; the final themes of use and trust overlap the initial 3 theme. Consumption is impacted by the data visualisation's ability to talk to the objective of the decision and the ability of the technology used to map the mental model and thinking processes of the decision-maker. Furthermore, data visualisations must not only identify the best decision, but also help the executive to define actionable steps to meet the goal of the decision. Executives appreciate the knowledge and skill of peers and prefer an open approach to decision-making, provided that each inclusion is to the benefit of the organisation as a whole. Benchmark statistics from similar industries also add to the consumption factor. Speed was only defined in terms of the data visualisation design, including the use of contrasting elements, such as colour, to highlight anomalies and areas of interest with greater speed. Furthermore, tolerance limits can also assist the executive in identifying where thresholds have been surpassed, or where areas of underperformance have occurred, focussing on problem areas within the organisation. Finally, confidence is not only impacted by the data visualisation itself but is also affected by the executive's knowledge of the decision and the factors affecting the decision, the ability of the data visualisation presenter to understand, guide and add value to the decision process, the accuracy and integrity of the data presented, the familiarity of the technology used to present the data visualisation and the ability of the data visualisation to enable explorative and collaborative methods for decision-making.

RQ3: What elements should data analysts consider when developing data visualisations?

Based on the findings, to answer RQ3, the trust theme identifies qualitative factors, relating to the presenter. The value, consumption and confidence themes all point to the relevance of having an open and collaborative organisational culture that enables the effective use of data visualisation. Collaboration brings individuals together and the power of knowledgeable individuals can enhance the final decision. In terms of the presenter, his/her organisational ranking, handling of complexity and multiple audience requirements, use of data in the data visualisation, ability to answer questions, his/her confidence and maturity, professionalism, delivery of the message when presenting, knowledge of the subject presented, understanding of the executive's objectives and data visualisation methodology, creation of a "WOW" factor and understanding the data journey are all important considerations.

In relation to the conceptual model identified in Figure 11, the results of the interviewee responses are transposed onto the conceptual model (Figure 11), with a symbolic key per theme (value, trust, consumption, speed and confidence). The symbol highlights where each theme, a collective of interviewee responses, are supported by the conceptual model designed by the researcher. Additional observations are discussed in the Discussion section, section 6.2.

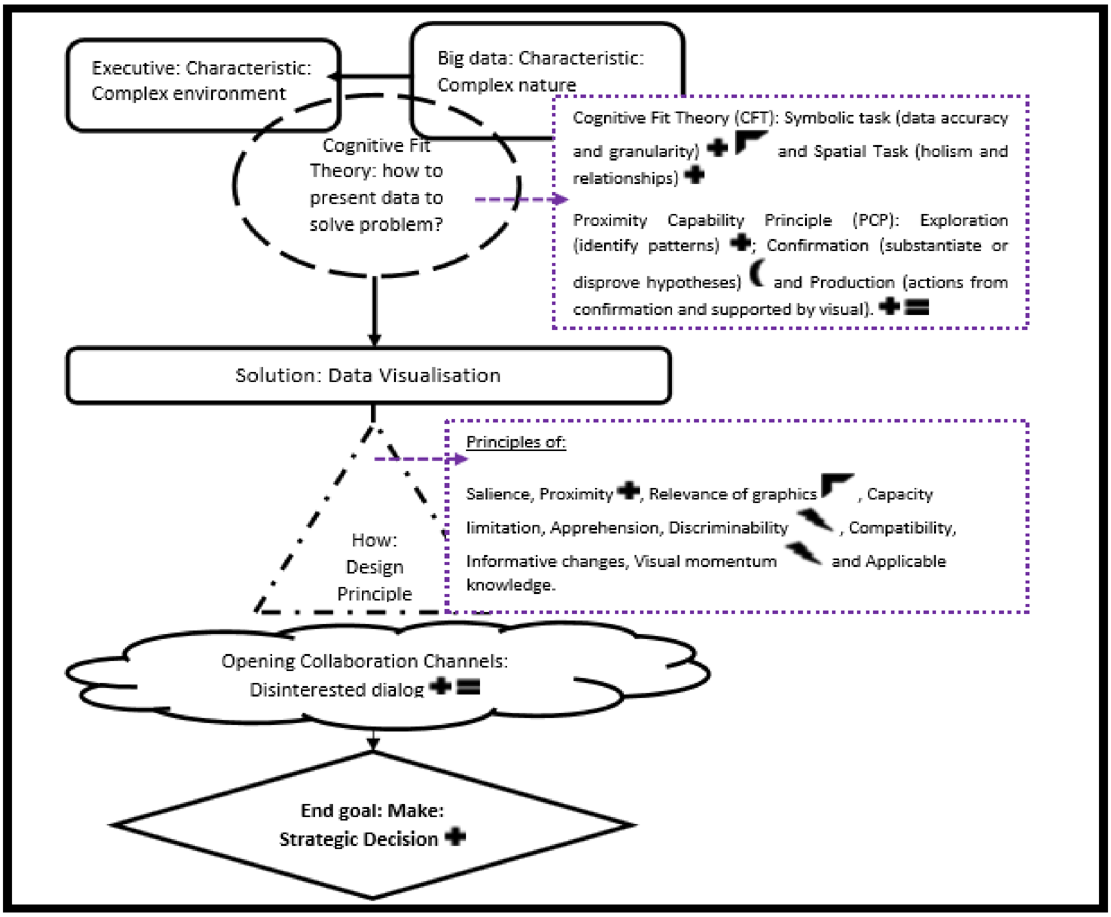


Figure 224a Conceptual Model with themes from interviews.

Key interviewee results transpose onto the conceptual model:

Key:

Themes:

Value – understanding premise of data source and data journey onto data visual; multi-dimensional data view; data accuracy; data visualisation intuitive-ness, clarity, insightfulness, ability to identify gaps, trends, patterns and implications and problem-solving ability; supports executive's objective; internal organisational culture data driven-ness; collaborative properties; capability to implement decisions; and executive's familiarity with data visualisation technology.

Trust – understanding data journey onto data visual; ability to prove and disprove executive's hypotheses; and data presenter's effectiveness and knowledge of subject under discussion and executive's business

Consumption – ethical and effective use of data in data visual; data visualisation intuitive-ness, clarity and insightfulness; supports executive's objective; collaborative properties; capability to implement decisions; and executive's familiarity with data visualisation technology

Speed - contrasting variables used on data visualisation

Confidence - understanding premise of data source and data journey onto data visual; supports executive's objective; collaborative properties; executive's familiarity with data visualisation technology; data presenter's effectiveness and knowledge of subject under discussion and executive's business; eliminating superfluous and redundant data; identifying competitive advantage; timeliness of data and data quality, validity and integrity

Figure 235 Conceptual Model with themes from interviews key.

6.2 Discussion

The discussion included reflections regarding the research methodology, re-performance considerations and scientific contribution.

In terms of the methodological reflection, the study chose a qualitative method for the purposes of understanding critical views of executives and data analysts (Creswell, 2013; Lub, 2015). Other methods that were considered, but not used, include the quantitative methodology and mixed methods (Creswell, 2013; Patterson, 2011). The researcher did not believe that using either of these methods would have produced more efficient or accurate results, as personal views and experiences are produced from a subjective perspective, not through quantitative expression (Lub, 2015). In terms of data visualisations, the nature of these tools is not static and nuances can be implemented. If a quantitative study were to be performed, the researcher would have had to categorise each type of data visualisation, e.g. dashboard, bar chart and so forth, which could be infinite. Furthermore, the researcher used data visualisation as the dependent variable and it was never the objective to base the study on a particular data visualisation type. Rather, the approach adopted was to understand views and experiences relating to data visualisation use in a collective manner. However; if data visualisation types were referenced by participants, the researcher ensured that the data analysis included these examples. A key question considered by the researcher was whether the same results would be produced if the research study were re-performed. According to Myers and Newman (Myers & Newman, 2007), in qualitative research studies, it is not uncommon that answers may differ slightly, as different participants are introduced. However, to minimise inconsistency, results were obtained across a variety of executive and data analyst levels to prevent sampling bias as far as possible. Furthermore, qualitative research does highlight the uniqueness of individual responses and thus responses are not expected to be the same. Identification of differing individual experiences and knowledge allows for variances to be tracked to specific interviewees through dependability (Erlingsson, & Brysiewicz, 2013).

From a substantive and scientific perspective, prior literature reviews and research studies have not pointed out individual preferences based on a subjective perspective. In terms of identifying what visual principles are most efficient in a corporate environment, none were identified that related to strategic decision-making. This research study was able to extract information with regards to data visualisation value, trust, consumption, speed, confidence and use. Therefore, a different perspective among a collective group of organisational employees was formulated. It was also found that these themes can interrelate, and that varying considerations pre and post data visualisation presentation, such as determining the objective of the decision first and having a clear action plan to implement the decision with tracking ability, also have a bearing on data visualisation use. Therefore, the process of data visualisation design is not singular or linear, but rather multi-dimensional, multi-faceted and organic.

Findings from this research study can provide practical knowledge for data visualisation designers, but can also provide academics with knowledge to reflect on and use, specifically in relation to information systems (IS) that integrate human experience with technology in more valuable and productive ways. Academics can explore new ways of data processing and product design and development, while focussing on the distinct relationship between human cognition and IS.

6.3 Recommendations

Based on the literature review performed, much of the data visualisation research appeared in the health sciences industry, with little reference to data visualisation effectiveness in corporate environments. Further research within the IS field can include the effects of corporate culture on data visualisation use. Corporate culture is a concept that describes the corporate’s ethos, which has not been clearly referenced or defined in prior data visualisation literature (Schein, 2009). This research study did however identify that a collaborative culture can affect the decision-making process and that data visualisation must be able to open the communication channels in order to be effective. However; questions remain. If the corporate culture is dominant and autocratic, can data visualisation still serve as an effective decision-making tool? In these instances, could data visualisation bridge the gap between varying organisational strategies and employees to enhance corporate collaboration? Can data visualisation still be effective in non-data driven environments?

During this research, the researcher also became aware of the importance of human cognitive and sensory processes and its impact in IS development. The researcher believes that more focus can be placed on the psychological factors of technology acceptance. The current TAM model, used to describe use in this research study, identifies perceived usefulness and perceived ease-of-use as the primary considerations in technology adoption. However, factors that have been identified that impact on use do not express the importance of cognitive processes in technology adoption. For example, this research has identified mental modelling as a key consideration in limiting user fatigue, but how does this translate into technology design and acceptance? The purpose of information systems is to enable a richer, more productive and enabling experience for users. Technology trends are oftentimes developed from an idea generated from a single person, who pushes the technology solution onto people without consideration of future effects on human behaviour and confidentiality. However; as users become more technologically intelligent, the trend may turn to user-driven technology development, based on the interactions and experiences people would like to have. Therefore, IS should also focus on the intangible factors that can affect adoption and technology use.

In summary, data analysts should ensure that data visualisations presented to executives have a key, describing and bringing salient points to the fore. Data analysts should ensure that there is a pre-narrative to the presentation that identifies data sources used and why those data sources were chosen. It is best to have more than one data source, however; the number of data sources is dependent on the topic presented. Redundant data should not be included, and the data visual medium must fit the data form. The rules and formulas applied to translate the data onto the data visual should also be discussed, including why they were used. It is important to note here that data integrity is highly regarded by executives. Data accuracy, validity and timeliness are important factors to consider when making decisions, allowing the executive to gain greater comfort in his/her decision. Therefore, data source and rules applied to cleanse data is again paramount. Data analysts should ensure that the data visualisations follow graphic principles, such as those outlined by Hegarty (2011) and ensure there is a "golden thread" throughout the visual display. Data analysts should encompass the above suggestions into a data visualisation methodology, to be used for future initiatives. Presenters must also take note of their behaviour while presenting. Verbal and non-verbal communication can have an effect on the overall outcome of the data visualisation presentation. Confidence in the presenter's ability to understand the executive's business, objectives, requirements and knowledge of the topic presented must be clear and concrete. Presenters should also be well-prepared to answer questions that the audience may have, thus he/she should research the audience and the types of questions that would affect his/her objectives. Presenter's must also be cognoscente of the technology intelligence and knowledge of the audience. Therefore, complicated data visualisation solutions may not be effective if the audience has limited capacity to absorb the information in the manner displayed. Complex and highly animated data visualisations do not necessarily translate into data visualisation effectiveness. Finally, executives do not want the decision made by the data analyst. The role of the data analyst is to analyse the data and present it in an intuitive manner to allow the executive to make the decision. Therefore, the executive does not want to be led by the data analyst to a final decision, but rather as a guiding agent within the decision-making process, and to open the channels for debate and collaboration. In such instances, the executive wants to take accountability for his/her decisions, but relies on the data analyst for accurate, valid, timely, and where possible complete, data to make such decisions where insight for competitive advantage are paramount.

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APPENDIX 1: ACTUAL RESEARCH INSTRUMENT

The research questions were derived from practitioner interest and experience, with review performed by an experienced executive practitioner within the data visualisation realm.

Research Question	**Purpose of Question**	**Respondent**
RQ1: What do individual organisational executives value and use in data for strategic decision-making purposes?		
RQ1.1: In your role as Executive, how would you describe your data confidence level when using data for strategic decision-making and why do you say so?	The purpose of this question is to determine whether the confidence level of the Executive in using (big) data could impact on his/her ability to comfortably use data visualisation, as well as to indicate the Executive's level of use of data in strategic decision-making.	Executive
RQ1.2: In your role as Executive, and when involved with strategic decisions, how do you approach the strategic decision-making process and what factors do you consider, what influences you?	The purpose of this question is to determine what elements are used by the Executive in strategic decision-making, without pointing to data specifically, as other considerations may be relevant. Again, this question also points to the prevalence and perceived importance of using data strategic decision-making.	
RQ1.3: What considerations do you believe are critical and beneficial, or alternatively not critical and beneficial, when using data in strategic decisions? Please supplement this with examples of how you used data in a strategic decision.	The purpose of these questions is to identify data elements, whether tangible or intangible that may affect the Executive's strategic decision-making process. It is also aimed at determining if there is any consistently pertinent data that is required when making strategic decisions that should be included in data visualisations.	
RQ1.4: What information do you believe is missing, specifically when making strategic decisions? In other words, what would you like to see and use in your strategic decision-making process?	The purpose of this question extends from question RQ1.3, as it is also aimed at determining if there is any consistently pertinent data that is not visible to the Executive that is required when making strategic decisions that should be included in data visualisations.	
Research Question	**Question Objective**	**Respondent**

RQ2: How does data visualisation impact on an Executive's ability to use and digest relevant information, including on their decision-making speed and confidence?		
RQ2.1: Do you believe your level of IT (Information Technology) understanding and experience impacts on your capability to use data visualisation? Please substantiate your answer, with possible examples illustrating your point. What was it about the technology that hindered or enhanced your capability?	The purpose of this question is to determine whether or not the use of IT has an impact on the ability (confidence) and capability (speed) of executives to use data visualisations in strategic decision-making which are developed using information technology.	Executive
Do you believe that data visualisation is a "new age gimmick" or a valuable business tool? Please explain why, possibly using an example, or explanation, for either scenario relevant to you.	The purpose of this question is to gauge the experiences and feelings of the Executive when presented with data visualisations. This can relate to past and present data visualisations. The question is also aimed at identifying the reasons for the Executive's like or dislike of data visualisation.	
How would you envisage the use of visualised data in a strategic decision? Additionally, how should data be presented to you to expedite the strategic decision-making process under pressurised circumstances/conditions (e.g. time pressure)?	The purpose of the question is to understand what the Executive perceives as important and relevant in data visualisation by directing his/her critical thinking to future scenarios to visualise his/her requirements when under pressure.	
What are your key concerns when looking at a visual representation, such as a dashboard, for the first time?	The purpose of this question is to determine the thinking of an Executive when he/she is faced with a data visualisation and possibly pointing to his/her uncertainties with data visualisations that can give light to significant elements that data analysts must consider when developing data visualisations. The example of the dashboard is predominantly used in data visualisation and has been used to stimulate the respondent, but the question will not be limited to this data visualisation form.	
How have visualisations affected your strategic	The purpose of this question is to gauge the current perceived relevance of data	

decision-making process and strategic decision-making outcome? Has an insight that was obtained from a visualisation ever resulted in a significant strategic decision being made? If not, why do you believe the visualisation was not a contributor? Can you possibly provide an example for either scenario?	visualisation is strategic decision-making, to determine whether or no executives rely on data visualisation for strategic decision-making. If he/she does not, what are the reasons for this? Such explanations can assist the data analyst in improving on data visualisation design.	
Describe your level of trust when you see a data visualisation. When the insight that the visualisation provides does not align with your understanding, what are your immediate thoughts? Alternatively, when it does align, what are your immediate thoughts?	The purpose of this question is to demystify the premise that data visualisations cannot be trusted at face-value. Therefore, what aspects of data visualisations build trust, and further confidence, for its effective use for Executive strategic decision-making? Furthermore, this question is aimed at understanding how data visualisations impact on the Executive's ability to be open to different ideas that may be generated by data visualisations, which may also be dependent not only on individual personality but organisational culture as well. This has an impact on data visualisation usefulness.	
How often do you debate the insight provided by a data visualisation versus the accuracy and underlying premise (principle/idea) of the visualisation? Is it possible to provide examples to explain your answer?	The purpose of this question is to demystify the premise that data visualisations cannot be trusted at face-value. Therefore, the type and elements of data visualisation analysis by the Executive may influence data visualisation usefulness. This may also lead to further understanding of what type of data is relevant for data visualisations, such as data source.	
How often have you been involved in creating a data visualisation in order to more clearly articulate an insight, and if you have not been involved in this creation process, what aspects of data visualisation do you believe is important to be involved in and why?	The purpose of this question is aimed at understanding whether the level of past direct data visualisation experience impacts on the ability of the Executive to adopt data visualisation as a valuable tool. It also determines what executives believe is an acceptable level of involvement in data visualisations development, between no involvement to constant involvement which may impact on his/her level of trust and use of the data visualisation by the Executive.	
Is it possible that you feel you could do a data visual representation better on	The purpose of this question is to determine whether or not an Executive is likely to develop data visualisations on his/her own	

your own if only you had the appropriate training to do so, as opposed to another person creating it for you? Why?	given the adequate technical tools and “know-how” to do so. This can also determine whether or not data analyst involvement in data visualisation design has an impact on his/her level of data visualisation trust. This question could also indicate to some degree whether or not the Executive values data visualisation such that he/she is willing to spend time amidst his/her busy schedule to provide answers.	
How often does someone have to explain the visualisation/dashboard to you before it makes sense? Does this then impact on your perceived value, relevancy and usefulness of the visualisation? Why?	The purpose of this question is to determine whether or not there are elements in the data visualisation that deter Executive comprehension that data analysts may be unaware of, resulting in potential non-use of the data visualisation.	
How often do you provide recommendations for improvements to dashboards/visualisations and what are these common improvement recommendations that you provide? (Can examples possibly be provided and are any recurring themes identified?)	The purpose of this question is to further determine whether or not there are elements in data visualisation that impact on Executive comprehension and use, however directing the response towards potential solutions. By understanding the recommendations, data analysts can draw on these elements to contribute towards more effect data visualisation design.	
Do you have a preference for a specific type of visualisation e.g. the type of visual form (dashboard, interactive visual etc.) or visualisation design e.g. colours, shapes used etc. and do you believe that the visualisation type and design impacts on your ability and confidence to make faster strategic decisions? What is it about data visualisation that makes you believe this?	The purpose of this question is to further determine whether or not there are elements in data visualisation that impact on Executive comprehension and use, however directing the response towards data visualisation type. By understanding the elements impacting the Executive based on the type and other visible developmental elements, it could contribute towards more effect data visualisation design.	
Can you provide an example where you obtained insight from a visualisation that you were previously unaware of (e.g. an insight of value that	The purpose of this question is to determine whether or not data visualisation opens the Executive’s thought process outside the boundaries of his/her initial thoughts and assessments. It is also aimed at supporting the notion that data visualisation evokes	

benefited you in some way)? If not, why so?	discussion broadening understanding and creating a catalyst for dialogue. This is a significant consideration of strategic decision-making.	
Do you believe the following statement: “the analysis of a visualisation of data equates to being an insights driven organisation.” Please explain your answer.	The purpose of this question is to determine whether the data visualisation tool itself creates insights, or whether other elements foster driving organisational insight, such as human elements of experience. Therefore, this question aims to position the relevance of data visualisation within the Executive’s perspective.	
Explain an experience where you and a colleague saw the same set of data in a visualisation, but where you each interpreted it differently? How did this impact on your understanding of the data and how did it allow you to identify different views or raise questions?	The purpose of this question is to determine whether data visualisation is able to open creativity and dialogue amongst executives, by stimulating memory and drawing from past and current experiences. It also eludes to the possibility that the organisational culture, one that is collaborative and supports dialogue whereby participants are open to being challenged and airing views, may also impact on the usefulness of data visualisations.	
How often have you presented a visualisation where the Executive did not understand it? How then did you go about resolving this matter?	The purpose of the question is to obtain the view of data analysts in their data visualisation journey, who have first-hand experience of the reactions of executives and the types of responses they receive, whether it be positive or negative. This could collectively aid data analysts by sharing their experiences for particular data representations and the processes followed to effect necessary changes that may impact on the usefulness of data visualisations.	data analyst
How often do you have to explain what is being represented in the data visualisation? What component(s) do you need to explain the most, the visualisation or the underlying data and scripting?		
How often does the Executive disagree with the visualisation or recommend that different data elements be used? Do you typically agree with the feedback provided or not agree? If you do agree, what do you believe were the reasons that		

contributed to its misalignment and how did you rectify the situation? If you do not agree, why so?		
How often have you been told that a different type of visualisation would have worked better for a specific insight? Do you typically agree with the feedback? If yes, why? If not, why?		
Can you summarise the key challenges and successes that you have faced when initiating, completing and presenting a data visualisation? Please, if possible, could you provide examples of these situations and what you believe contributed to the success or challenge?		
How often do you feel that you are working without direction from the Executive? Why is this?	The purpose of this question is to gauge the relevance of Executive participation and what impact and relevance this has on the data visualisation journey and data visualisation acceptance.	
RQ3: Must data analysts include or consider intangible elements to data visualisation design?		
What are your perceptions of the technical person who developed the dashboards?	The purpose of this question is to determine whether or not the data visualisation creator and/or the data visualisation presenter has any impact on the level of trust and use of their data visualisation. Such elements could include the person's experience, trust, education and standing in the organisation.	Executive
How do you believe a data presenter's career history and education, their standing in the organisation and trust level impact on your perception and use of the data visual they present or is used?		
How do you approach data visualisation design and what factors or influences do you consider during this	The purpose of this question is to determine whether or not (in) tangible elements, and what factors, are considered influential in data visualisation, based on the data	data analyst

process? Please kindly provide examples if possible.	analyst's experience. Thus what factors are they aware of that can impact the audience usefulness of data visualisation?	
How do you feel about the statement that in order to design an effective data visualisation, the data expert/analyst must consider intangible factors in visualisation design, for example, human cognition and perception behaviour, the education of the visual viewer, experience of the visual viewer, personality of the visual viewer, culture of the organisation in which the visual viewer resides, social standing and influence of the visual viewer? In other words, do you agree or disagree that data visualisation design is more than just a contextual creation and is also a conceptual exercise which perhaps requires wider consideration of such factors during design? Why do you agree or disagree with this thought? Do you perhaps have any examples explaining your reasoning?	The purpose of this question is to further explore the relevance of intangible factors, if any, in data visualisation design. This is again based on the experience of the data analyst.	
Do you think that a better understanding of the business process or strategic direction and decision-making would help you in delivering better visualisations, and therefore better insights? What makes you believe your stance? Please kindly provide examples of where understanding the business process, strategic direction or decision-making helped, could have helped or did not help?	The purpose of this question is to add the processing element when developing data visualisations. It also eludes to determining the relevance of a broader understanding of the business/organisation that may impact on the data used in the data visualisation and resulting interpretations.	
Do you feel that the Executive requires more	The purpose of this question is to determine whether, in the data analyst's view, the ability	

training in understanding visualisations better or do you feel that you require more insight and general training in understanding the Executive role within the organisation or the Executive him/her-self better?	to use data visualisations more effectively and to aid in the understanding of the data visual itself and the manner in which it is constructed can be positively influenced by Executive training. Furthermore, this question is aimed at whether data analysts feel unequipped in dealing with executives, hence impacting on the usefulness of data visualisations created, as they do not understand the organisational role of an Executive and therefore unfamiliar with their needs and requirements.	
Do you have a preference for a specific type of visualisation? What are your reasons for using this type of visualisation (e.g. ease of use, a good understanding of the development technology etc.)?	The purpose of this question is to give light to data visualisation factors that may impact on the data analyst's ability to effectively communicate the data to the Executive in a meaningful manner and that perhaps certain types of data visuals are more beneficial than others in relation to the data to display.	